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Variation in treatment
an analysis of dental radiographs using matched patient provider data

Elouafkaoui, Paula

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Variation in Treatment: An Analysis of Dental Radiographs using Matched Patient Provider Data

Paula Elouafkaoui

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List of Abbreviations

BDA	British Dental Association
BHPS	British Household Panel Survey
CDS	Community Dental Services
CECS	Centre for Evaluative Clinical Services
CHI	Community Health Index
CoT	Course of Treatment
DDRB	Doctors' and Dentists' Review Board
DEPCAT	Deprivation Category (Carstairs)
DHSRU	Dental Health Services Research Unit
DHSSPS	Department of Health, Social Services and Public Safety
DoH	Department of Health
DTI	Department of Trade and Industry
EDI	Electronic Data Interchange
FE	Fixed Effects
GDS	General Dental Services
GP	General Practitioner
HDS	Hospital Dental Services
HEAT	Health Improvement, Efficiency, Access and Treatment
HIC	Health Informatics Centre
HMOs	Health Maintenance Organisation

ISD	Information Services Division
LEHD	Linked Employer-Household Dynamics
LSDV	Least Squares Dummy Variable
MIDAS	Management Information and Dental Accounting System
NHS	National Health Service
NPD	National Pupil Database
OLS	Ordinary Least Squares
PCT	Primary Care Trust
PDS	Personal Dental Services
PSI	Policy Studies Institute
PSD	Practitioner Services Division
RE	Random Effects
SDPB	Scottish Dental Practice Board
SDR	Statement of Dental Remuneration
SDRS	Scottish Dental Reference Service
SIMD	Scottish Index of Multiple Deprivation
SMR	Scottish Morbidity Record
UDA	Units of Dental Activity
UK	United Kingdom
US	United States

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Declaration

I declare that I am the author of this thesis; that, unless otherwise stated, all references cited have been consulted by me; that the work of which this thesis is a record has been done by me, and that it has not been previously accepted for a higher degree.

Paula Elouafkaoui

Summary

Variation in health care, whether it be in terms of the utilisation of resources, observed health outcomes, costs, quality or access to health care is a well recognised and ever present feature of the modern day health care system. Health care variations challenge basic assumptions about the nature of the health care economy and raise questions about efficiency, equity and where best to direct policy instruments in health care markets. Despite the vast literature documenting variation, and the many discussions around ways to reduce variations in health care markets, the field of dental care has received little interest, in comparison to that of general medical care. This thesis will address this gap and will analyse the variation observed in a specific dental care treatment (dental radiographs) within NHS Scotland, with particular emphasis on the contribution of both dentist and patient unobserved heterogeneity.

The thesis takes its focus from two strands of the literature; the underlying theoretical aspect draws on the literature concerning the theory of incentives and physician agency, whilst the empirical component makes use of recent advances in micro-econometric methods, documented in the labour economics literature. Although the thesis is predominantly an empirical analysis, the estimation strategy combines ideas from both the theoretical and empirical literature. A matched patient provider dataset from NHS Scotland is used to conduct an analysis of the variation in dental radiographs, in the presence of, and controlling for unobserved dentist and patient heterogeneity.

The results indicate that the remuneration structure alone has little or no impact on the treatment decision to provide a radiograph. When a dentist changes

from being on a fixed salary contract to being paid on a fee-for-service basis, they are in fact less likely to provide a radiograph. This result changes in the presence of insurance (identified as being when patients are exempt from the patient charge) and indicates that when the self employed dentist can identify the patient as being exempt, they are more likely to provide a radiograph. This result provides some support for the theory that in the presence of insurance, financial incentives do influence the treatment decision.

A final result of the study highlights the importance of accounting for unobserved patient *and* provider heterogeneity, a factor that has had little attention in the healthcare literature. The results suggest that patient variation, as opposed to the variation across dentists, is much more important in explaining total variation. This is a similar result to that found in both the labour and education literatures.

Chapter 1: Introduction

1.1 Introduction

Variation in health care, whether it be in terms of the utilisation of resources, observed health outcomes, costs, quality or access to health care is a well recognised and ever present feature of the modern day health care system. There is evidence documenting its existence in all sectors and across all levels of the health care delivery process, for example across regions, demographic groups, health care institutions (hospitals, GP practices), and across individual health care providers within the same institution. In a world where health care costs continue to rise at alarming rates and with little evidence to suggest this is matched by improvements in the quality of care (Fisher et al, 2003; Wennberg, 2008; Gawande, 2009), Governments and health care providers are forced to address the issue of variation.

Health care variations challenge basic assumptions about the nature of the health care economy and raise questions about efficiency, quality, equity, and where best to direct policy instruments in health care markets. It is a longstanding view that economists are concerned with the traditional welfare loss associated with health insurance; however there is growing concern in the literature about the welfare loss associated with variation, and what it means for health care expenditure (Phelps & Mooney 1993; Phelps 1995). Grytten & Sørensen (2003) are of the opinion that the welfare loss resulting from variation in clinical practice between physicians may be just as great as that observed in the markets for health insurance.

In a literature that spans more than 60 years, the same theories are consistently used to explain the observed variations in health care delivery, practice and performance. Featuring high on the list is the concept of physician practice style, the impact of economic incentives, and more recently the recognition of the importance of patient specific factors (observed and unobserved) in accounting for variation has become apparent. Despite the vast literature documenting variation in general health care, there has been relatively little attention given to the field of dental care.

Many of the investigations that do consider dental services do so in the context of area or regional differences in the patterns of use of care (Grembowski et al. 1991 provide a review). This is often in terms of the average number of services provided or simply based on whether the patient visited a dentist or not. It is difficult to gain a clear understanding of the major contributors to variation in these studies as the effects are often interlinked with each other and not easily separated. This gap in the literature is one that this study will address.

One of the main aims of this study is to try and account for as much of the variation in the provision of a single dental treatment (radiographs) as possible. A key focus is placed on controlling for both individual patient and dentist characteristics. There are a very limited number of studies in the field of dental care that have considered the variation in the provision of dental radiographs, and there are none to my knowledge that use a framework similar to the one being adopted in this study.

Rushton et al. (1999) considered the factors influencing the selection of panoramic radiographs and Rushton & Horner (2006) conducted a similar study to identify the factors that influence the frequency of bitewing radiographs in general dentist practice. Both studies were based on self reported questionnaires completed by dentists that asked questions about their provision of radiographs and about their attitudes and beliefs towards the usefulness of radiographs as a diagnostic tool. There were some questions included to elicit patient characteristics as well as dentist characteristics, but both analyses were conducted more from the dentist perspective. In a study by Gilbert et al. (2006) the relationship between practice characteristics and patient receipt of dental diagnostic radiographs is explored. This study did take account of individual patient characteristics, but this was a mixed methods approach that involved interviews with dentists and a review of patient records over a four year period. Again, all the likely contributing factors to the variation in the receipt of radiographs have not been considered simultaneously in a single estimation framework. Essentially this aspect sets this study apart from anything that has been done before.

Chalkley & Tilley (2006); Chalkley et al. (2010) and Young (2009) have considered the impact of different payment structures on the treatment decisions of dentists in the UK. All find some support for the idea that under a fee-for-service remuneration contract, dentists are motivated to some extent by potential financial gains. This thesis derives its focus from these empirical studies, but also from the labour economics literature on matched employer-employee data. Whilst the studies identified above have considered dentist behaviour in the context of overall treatment intensity, this study differs in that it analyses and explores the variation in the provision of a single treatment, i.e. dental radiographs.

The Chalkley & Tilley (2006) paper was concerned with the influence of remuneration contracts on the quantity of dental services provided. They recognised that the effectiveness of remuneration in influencing outcome is an empirical question; the challenge is to isolate the effect of remuneration in the presence of other factors such as the unobserved heterogeneity of physicians and their patients. In this study both patient and dentist specific effects were controlled for in a multi-level random effects model. It was discussed that whilst they had gone some way towards controlling for patient heterogeneity, more could be achieved within a matched patient-provider fixed effects framework. This was beyond the scope of that particular study, thus this study picks up on this point and aims to apply the fixed effects framework described within. This study will also consider the influence of the remuneration contract on the provision of radiographs; with a view to finding out if there is a difference between a single treatment item and a bundle of treatment items.

The data collected in Scotland on dental care provides a highly functional high quality dataset with a structure and features that can assist greatly in producing empirical evidence on the variation in health care.[1] The aim of this study is to exploit the data, with a view to being able to analyse the variation that exists across treatments. As mentioned, in this study, the choice of treatment to analyse was that of dental radiographs. An initial look at the data revealed that there was widespread variation in the use of radiographs across General Dental Services (GDS) dentists in Scotland (Figure 5.1). This distribution shows the likelihood that each dentist will provide a radiograph in any given course of treatment. The majority of dentists will provide radiographs anywhere between 10 and 40% of the time, whilst almost 4% of dentists almost never provide radiographs. However there are small proportions that tend to provide them much more often, with some dentists having almost all their

[1] A detailed description of the data is given in Chapter 5

courses of treatment containing one of these small film radiographs. The data alone therefore provides some motivation for further study of radiographs. The fact that so little research has been done in this area provides further motivation to look at radiographs. Is there some belief or expectation that dental radiographs would not exhibit the kind of variation across dentists that the data suggests there is?

Wennberg and others (Wennberg et al. 1982; Wennberg, 1984, 2010; Evans 1990) found that typically variability is common when there is uncertainty or lack of knowledge about a procedure or treatment, in terms of its use or the potential costs/benefits to patients. These factors would not appear to be typical in the case of dental radiographs. The benefits of radiographs in dentistry have been known for many years and their use has become standard practice in the field of dental care. Another aspect applicable in the case of radiographs is the fact that their use is somewhat regulated. Guidelines are in place about when and how often radiographs should be carried out and dentists have certain protocols to follow when making the decision to give a patient a radiograph (National Radiological Protection Board, 2001). This makes the case of dental radiographs an interesting one to consider and the available data makes it quite easy to assess the provision of radiographs by dentists. A detailed description of the data collection and processing is given in Chapter 5. This helps to explain further where and how the use of radiographs fits into the dental care system. For now it is useful to know that in the data, a radiograph is a separate item with an associated fee, and dentists will receive payment for every radiograph carried out. Approximately 1.3 million radiographs were carried out in Scotland in the financial year ending March 2010 (SDPB, 2010).

Dentists are paid £4.00 for each small film radiograph and up to a maximum of £16.50 for additional films.

The existence of variation and the other factors surrounding the provision of radiographs makes them a suitable treatment for analysis. The aim of this study is to use a micro-econometric modelling strategy in order to explain why this variation exists. The typical questions that will be addressed are, 'what are the sources of this variation' and 'how much does each source contribute to the overall observed variation in radiograph provision'.

To fully account for the variation in the use of radiographs, it is necessary to do so in a way that can consider the impact of economic incentives. Economists are often concerned that in the presence of information asymmetry in health care markets, there may be an incentive for providers to provide treatment that the perfectly informed patient would not have chosen. This can lead to a result where the treatment decision may not necessarily be in the best interest of the patient. This presents another motivation for the decision to investigate dental radiographs, given the nature of the treatment in terms of the potential risks to health.

Radiographs are without doubt an invaluable diagnostic tool, but are also, not without risk. Although the dose of radiation is low in dental radiographs, the effects of radiation exposures are cumulative and therefore depend on the total amount absorbed throughout ones' lifetime. Today, with technological advances people are absorbing increasing amounts of radiation from their natural environments and so any exposure, however low the doses, should be limited wherever possible. Radiographs should only be given when needed and when the benefit far outweighs the potential risk (National Radiological Protection Board, 2001).

Numerous studies in the literature have investigated the potential risks associated with dental radiographs, with a particular view to establishing a possible link to certain types of cancer. The evidence is somewhat conflicting and the consensus is that it is very difficult to ascertain one way or another if dental radiographs are a contributing factor in the development of some forms of cancer. Some studies have, however, provided evidence in support of the idea that there may be some kind of link (however small) between the two (see for example, Berrington de González & Darby 2004; Preston-Martin et al. 1985. More recently Memon et al. (2010) claimed that the risk of developing thyroid cancer increases with the number of dental radiographs taken. Although this finding comes with a number of caveats, the researchers suggest that it might be time to review the use of dental radiographs as an evaluation measure for new patients and as a routine periodical procedure (usually every 6-12 months), particularly in children. It may not be possible to definitively claim that exposure to radiation from dental radiographs causes cancer, however there is definitely some agreement among the profession that 'no' radiation is 'good' radiation and that steps should be taken to ensure radiation exposure is minimised.

Dental radiographs therefore present a case where it is of particular importance to understand the sources of variation in their use, with a view to ensuring that patients are not being exposed unnecessarily to radiation. On the flip side it is also important to ensure that radiographs *are* being provided when clinically necessary as they can be used to diagnose a number of dental conditions. It is also a risk that if radiographs are not used when appropriate that things may be missed, resulting in patients requiring further and possibly more complex treatment in the future. These are all factors that have to be considered when trying to measure and understand the variation in the provision of radiographs.

1.2 Thesis Outline

This section presents a brief outline of the thesis and describes the main components of each chapter. Chapter 2 presents background information on variation in health care. A review of the literature is presented with a view to eliciting the major sources of variation and how variation has typically been analysed and measured.

Chapter 3 provides a detailed description of the origins and development of the empirical methods that will be used in the analysis. Particular attention is drawn to the labour economics literature and the use of employer-employee datasets (Abowd and Kramarz, 1999a; Abowd, Kramarz and Margolis, 1999). Issues around identification and estimation of the model are discussed and a practical solution to the problem is presented (Cornelissen, 2006). The work of Andrews et al (2006) is used as a starting point to develop a general model specification for estimation, adapted to a health care context with dentists and patients as the units of analysis. A simple principal agent model of physician induced demand is presented to motivate the empirical estimation in Chapter 5.

Gaynor et al (2001) discussed the importance of having detailed knowledge of the institutional context when conducting analyses that study physician behaviour. Chapter 4 provides such information and helps inform the development of the empirical model and the interpretation of its results in Chapter 5. In terms of the institutional framework, particular attention is given to describing the contractual arrangements of the dentist and the payment structure faced by patients.

Chapter 5 describes the data and presents the empirical analysis of the variation in the use of dental radiographs across GDS dentists in Scotland. A particular aim of this study is to investigate variation in treatment in the presence of and controlling for individual dentist and patient heterogeneity, both observed and unobserved. As indicated in Chapter 3, and highlighted by Gaynor et al (2001) the structure and quality of the data is central to being able to conduct this type of analysis. The empirical analysis makes use of what is essentially a matched patient provider dataset, taken from routinely collected administrative data used to process the payments made to dentists. Taking advantage of its unique panel structure and using the estimation method described in Chapter 3, the data is used to estimate a series of fixed effects models which control for individual dentist and patient effects, both separately and then together in a three-way error components framework.

Finally, in Chapter 6 the overall conclusions from the thesis are reported. The implications of the study in terms of policy are discussed and some suggestions on future avenues of research in this area are given, particularly in the context of the identified individual dentist *and* patient unobserved heterogeneities.

Chapter 2: Variation in Health Care

2.1 Introduction

Variation in health care has been defined as *"...the observation of differences in the way apparently similar patients are treated from one health setting to another"* (Hannan 1999). Variation presents itself in many forms and across many levels of the health care sector, for example, in the use of health care resources, health outcomes, costs, quality and access to health care. It has become a well recognised, ever present feature that impacts on all sectors of the health care delivery process. This Chapter continues with a review of the literature on variation. Section 2.2 provides historical background on variation and describes the key research that has been done in this field. Sections 2.3 and 2.4 identify the main sources of variation and describe how variations in health care have traditionally been analysed and measured. Finally Section 2.5 concludes.

2.2 Variation in Health Care: Background

There is evidence of variation existing across regions, demographic groups, health care institutions (hospitals, GP practices), and across individual health care providers within the same institution. These variations arise from the balance of interactions between patients, physicians and the wider health care organisation. Such interactions ultimately impact on health care management decisions which in turn determine factors such as the quality, cost, and supply of care delivered to individual patients. The health care system is a complex organisation with complex interactions between its many components, making it impossible to analyze some without the others (Dodgion & Greenberg 2009).

Dodgion & Greenberg (2009), recognise that variation is a phenomenon that is certainly not isolated to the field of health care. It is *"...observed throughout society as a natural and inevitable attribute of all physical activities and events for which no single cause can be found".* The concept of variation in health care is not a new one and it has been documented for many years. The first systematic account of practice variation came in the form of a report by a British physician (Glover 1938) on the incidence of tonsillectomy among school children in England and Wales. Glover found widespread variation (tenfold) in tonsillectomy rates from one area of the country to another. The focus of the paper was not specifically aimed at analysing the economic consequences of such variation, but more to identify its existence. Glover did however reveal a startling result; for every death caused by the complications associated with tonsillitis itself, there were at least 8 deaths caused by the removal of the tonsils. Regardless of the economic issues, this observation presented a clear need to question practice variation, at least on ethical grounds if not on economic grounds.

Following Glover's exposure of the variation in tonsillectomy rates, there was a number of intervening studies aimed at investigating the issue of practice variation further. Glover (1948) followed up on his 1938 study, with an aim to provide guidance on how to deal with variation in tonsillectomy rates, from the paediatrician perspective. Lembcke (1952) considered the variation in appendectomy rates, as did Lewis (1969), along with regional rates of variation for five other common procedures. All studies continued to find results similar to Glover (1938), i.e. widespread variability across regions.

In the late 1960s Professor John E Wennberg began analysing US Medicare[2] data with a view to determining the performance of hospitals and doctors. In a statement to the Managed Healthcare Executive (McCue 2003), Wennberg stated, "*Our results were fascinating, because they ran completely counter to what conventional wisdom said they would be. .... When we looked at the data, we found tremendous variation in every aspect of healthcare delivery, even among communities served by academic medical centres. The basic premise - that medicine was driven by science and by physicians capable of making clinical decisions based on well-established fact and theory - was simply incompatible with the data we saw. It was immediately apparent that suppliers were more important in driving demand than had been previously realised".* Wennberg's early work centred mainly on geographical variation and the resulting variation in health care costs. At the time these ideas were largely unknown and remarked upon, apart from the few studies that followed Glover (1938). Wennberg was instrumental in pioneering work in this field and has continued to do so over the last four decades. In 1988 he founded the Centre for Evaluative Clinical Services (CECS) at Dartmouth Medical School (now known as The Dartmouth Institute for Health Policy and Clinical Practice) and was the founding editor of the Dartmouth Atlas of Health Care.

The Dartmouth Atlas of Health Care is a series of reports on how health care is used and distributed in the United States. The work at Dartmouth began by considering variation across geographical regions (small areas) usually in the context of the frequency in which various common surgical procedures took place. Wennberg and his colleagues continued to find systematic and persistent differences

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[2] Medicare is a state financed health insurance program for those aged 65 and over in the United States

in the standardised rates of use for these procedures (typically surgical removal procedures such as the appendix, tonsils, hernia, and gall bladder), but also in other medical services in the US (Wennberg & Gittelsohn 1973, 1982; Wennberg 1982; Wennberg et al. 1987). The main focus of the Dartmouth work is on the Medicare traditional fee-for-service patients; however several state-based studies of all health insurance claims (both Medicare and commercial) also show that the variations in resources and quality in the non-Medicare populations closely resemble those in the Medicare population.[3] This implies that the experience of the Medicare patients is a reliable predictor of the experience of the non-Medicare population.

As the study of variations in health care continues to grow and develop, this has forced the issue of variation to become an integral part of the agenda for any health care organisation aiming to improve service, whether in terms of efficiency or quality outcomes. A critical starting point is to recognise the existence of variation and understand the potential consequences. Variation in treatment decisions gives rise to variations in costs, utilisation of services and quality of care and outcomes. Wennberg was driven by the notion that it was important to understand and identify medical practice variation because it suggests a misuse of care (Wennberg 1984). He was the first to make the distinction between ‘warranted’ and ‘unwarranted’ variation and defined variations as being unwarranted if they cannot be explained by type or severity of illness, by patient preferences or the dictates of evidence based medicine.

[3] For example see the Atlas reports on Pennsylvania (1998), Virginia (2000) and Michigan (2000).

2.3 Categories and Sources of Variation

Although variation in healthcare presents itself in many forms and at different levels of the healthcare sector, it is useful to consider it in terms of two main categories. The first considers variations in the utilisation of services, whilst the other is related to variations in health outcomes. Within each category the sources of variation and potential ways to influence the variation are different. Sections 2.3.1 and 2.3.2 below summarise these categories and identify the main sources of the variation in each.

2.3.1 Variations in Utilisation of Services

One of the main causes for this type of variation is due to differences in the approach to *preference-sensitive* care, either at the patient level or the physician level. Wennberg (2002) defines preference-sensitive care as that for conditions where there are different options for treatment and where the choice between the options may carry different costs, benefits and risks. Typically patients' attitudes towards the health outcome in question will be different and warranted variation in the utilisation of services will and should exist as a result. Examples include the use of lumpectomy or mastectomy in treating early stage breast cancer, or the use of bypass surgery for treating heart disease. The unwarranted variation arises when the treatment decisions are influenced by factors related to the attitudes of the physician and local medical opinion, and not due to patient preferences. Wennberg (1984) referred to this as the 'practice style' factor and suggests that much of the variation in preference sensitive care is actually explained by the practice style of individual physicians. Different practice styles are thought to reflect a number of things such as differences in knowledge, training, health care environment and the interpretation of requirements. In some instances a lack of the necessary scientific information can lead to uncertainty among physicians about the appropriate treatment, though in many cases the practice style factor appears unrelated to scientific controversies (Wennberg 1984).

Not only is physician behaviour in terms of practice style a contributing factor in explaining variation in the utilisation of services, but other factors in health care markets, such as physician market power and financial motives, can also explain why physicians can influence treatment decisions, thus resulting in unwarranted variation. McGuire (2000) describes these factors under the umbrella term of 'physician agency' and discusses the mechanisms physicians can use to influence the quantity of care provided to patients. For example, in the presence of asymmetric information physicians can take actions to influence patient preferences. This phenomenon is referred to as supplier (physician) induced demand, whereby the physician is able to influence the demand for services in a way that the informed patient would not choose. Wennberg et al. (2007) found evidence of this when they found that the amount of care that would be demanded under shared decision making might be substantially less than what is actually provided. The question that needs to be addressed when considering this type of variation is whether or not the physicians recommended course of treatment corresponds closely to the patients informed preference. It is believed that medical practice that reflects physician agency will persist until patients are actively involved in the decision process and there are incentives for physicians to adopt shared decision making, as opposed to incentives that encourage financial gains.

The second main source of variation in the utilisation of services is due to variations in *supply-sensitive* care. It is often the case that many clinical decisions seem to be subtly influenced by the supply or availability of a particular service or resource (NHS Confederation 2004). The Dartmouth Atlas Research suggests that variations in supply-sensitive care may represent an overuse of medical services and the frequency at which these services are used is not determined by well articulated medical theory, or scientific evidence (The Dartmouth Atlas Project 2007b). This type of variation is particularly apparent in the management of chronic illnesses where physician visits, hospitalisations, stays in intensive care, and imaging services are all examples of care where the local supply influences the frequency of use. Typically when there is more capacity in the system more care will be delivered, whether this is warranted or not.

In the US this type of variation can be used to 'explain' most of the variations in Medicare's per capita spending among US regions (The Dartmouth Atlas Project 2007b). Of even greater importance to health care organisations and providers is the fact that research repeatedly shows that higher spending on health care and greater utilisation of services does not achieve better outcomes, in terms of quality of care or longer years of life (Wennberg et al. 2008; Gawande 2009). The Dartmouth Atlas, over the course of its research, has shown that death rates in areas where there is less capacity and utilisation are not higher than in areas where there is much higher capacity and utilisation. Fisher et al. (2009) actually found evidence of higher mortality in high resourced, high utilisation areas than in low resourced, low utilisation areas.

2.3.2 Variations in Outcomes

Health outcomes can be measured in a variety of different ways, for example in terms of mortality rates or improvements in morbidity. In the case of dentistry, the main outcomes of concern are dental caries (measured in children by the mean rates of decayed, missing and filled teeth), the prevalence of periodontal disease and the rates of oral cancer. Regardless of the field and method of measuring health outcomes, there is evidence of widespread variation across patients/physicians/hospitals etc. This type of variation is often the result of, or related to variations in the use of *effective-care*, where effective care is that which includes services whose effectiveness has been proved in clinical trials or well designed cohort studies (The Dartmouth Atlas Project 2007a). In other words there exists a sound medical evidence base to show that the benefits of use far exceed any potential harm, and there is no substantial trade-offs (in terms of risks) that depend on patient preferences. If this is the case, the view is that all patients in need should receive this treatment/service.

Variations in the use of such treatments reflect a failure to deliver needed care or the underuse of care, and in many instances the observed variation in many health outcomes can be attributed to this source. In the UK this type of variation has been in the media spotlight in recent years, where the term ‘postcode lottery’ has been used to describe the use of, or access to a number of health care services, particularly in relation to the use of cancer drugs and access to mental health drugs and services (BBC NEWS 2008; Cordon 2008; The Guardian 2009; Goodchild & Owen 2006).

2.4 Analysing and Measuring Variation

The vast majority of the studies on variation identified above have used small area analysis as a method to describe how rates of health care use and events vary over well defined geographical areas. Significant variations have been shown to exist in the rates of hospitalisation and in surgical procedures (Roos et al. 1986; Blais 1993; Brook et al. 1984; Chassin et al. 1986; Wennberg 1984) and that this is an international phenomenon (McPherson et al. 1982; Appleby et al. 2011). In these studies the unit of analysis has most often been small neighbouring areas, where it is assumed they are homogenous with respect to factors which influence health care utilisation, such as the underlying health status of the population and economic factors such as income and price. In some instances the variation has been measured across hospitals (Blais, 1993) within the same area.

Stano (1993) identified some methodological concerns associated with small area variation studies, particularly in terms of defining the small areas themselves, defining the at-risk patient population and ensuring the casemix in each area was similar. He re-evaluated the role of small area studies and suggested that there are many factors in accounting for inter-area variation, other than practice style (as suggested by Wennberg 1984). Small area variation studies and those which use aggregated data, use the practice style hypothesis to explain the observed variation, however they often don't include a clear definition of what is meant by practice style or provide any definitive measure of how much practice style contributes to the observed variation. Statements are simply made about the importance of practice style and that this can account for any 'unexplained' variation; however it could be argued that it is impossible to distinguish these effects from other influences, not only on the supply side, but also on the demand side (for example patient preferences).

Grytten & Sørensen (2003) considered further the practice style theory proposed by Wennberg to see if it could account for GP practice variations in Norway. They argued that improvements in the analysis of variation could be made and suggested that identifying practice style effects and their contribution to observed variation can *only* be achieved by conducting analyses at the individual physician level as opposed to studies that use data aggregated to the area/hospital level. In doing so they found that GP practice styles were an important determinant in explaining clinical practice variation and in turn expenditure on primary care services. They did however point out that the unexplained variation (after controlling for observed characteristics of the patients) represents an *upper* limit that variation in practice styles has on expenditure. They recognise the potential for overestimating the impact of practice style, which would be the case if for example, the patient population per physician varied with respect to health care needs.

The idea that physician effects were likely to be the most influential factors in explaining health care variations led to a change in the focus of studies attempting to account for variation. The literature saw a movement towards analysis at the physician level, but studies also emerged that used patients as the unit of analysis. (For a review refer to Vliet 1992; Newhouse 1994) As Grytten & Sørensen point out, a common finding is that patient characteristics such as age and gender can only account for a small proportion (approximately 1%) of the variation in observed health care outcomes or expenditure. Including other variables that reflect a patients underlying health status increases the proportion of variation attributable to patients to approximately 15%.

In the last 20 years, the existence of variation within the health care sector has continued to be documented and very recently a similar Atlas to the Dartmouth Project has been produced for England (DoH 2010).[4] Investigations have considered variation in terms of the frequency of treatment, the types of treatment, the cost of treatment and quite often look to the characteristics and the behaviour of the physician as ways to explain observed variations. One such strand of the literature considers the theory of supplier induced demand (Wennberg et al. 1982; Gruber & Owings 1996; Carlsen & Grytten 2000; Grytten & Sørensen 2001) to account for physician behaviour. In these studies, the focus is on the physicians being motivated by financial gain, although there is a growing literature that debates this idea and suggests that physicians are motivated by factors other than pure economic incentives. For example, Hausman & Le Grand (1999) propose that behaviour to a large extent is influenced by professional norms and the fact that physicians show some level of benevolence towards their patients. Fuchs (2000), in his discussion about the future of Health Economics, discussed how social norms can affect consumer demand, labour force participation, employer-employee relations and many other levels of economic interactions. He recognised professional norms as being an aspect of social norms and proposed they are of particular importance in health care.

As the evidence base grows on identifying factors that can account for variation it is now widely accepted that not only is it physician and supply side

[4] The NHS Atlas of Variation in Healthcare: Reducing unwarranted variation to increase value and improve quality can be accessed at http://www.rightcare.nhs.uk/atlas/

factors, but also patient, and demand side factors that impact on treatment decisions and health care outcomes. More recently, studies have extended to consider the relationship between individuals (patients or physicians) and the characteristics of the institutions to which they belong. Advances in statistical techniques and methodology have meant that now studies of variation in health care can combine these factors.

For example, multilevel models are becoming increasing popular to study variation in health care, particularly in the field of epidemiology. For a review of their benefits in health related research and examples of where they have been used, refer to Rice & Jones (1997); Duncan et al. (1998); Catalán-Reyes & Galindo-Villardón (2003).[5] Multilevel models make use of the natural hierarchical structure of the data commonly found in health care markets, where there are multiple micro units (patients) within multiple macro units (hospitals). It is then possible to make inferences and explore the variations at each level, with a view to being able to better account for the observed variations in medical practice. This type of modelling strategy enables the researcher to take account of the heterogeneity between individuals and between the higher level macro units.

To summarise, this section shows that the following factors are important determinants in accounting for the variation in healthcare and treatment:

- Institutional structure
- Physician practice style
- Financial incentives

[5] For more information Diez Roux (2002) provides a detailed glossary of the key concepts and terms used in multilevel analysis.

- Insurance contracts
- Underlying health status of patients and casemix
- Professional norms
- Physician and Patient preferences

From the literature, the standard approach is to consider variation in healthcare by considering many of these factors separately. For example, some studies will consider the impact of incentives in accounting for variation, others might analyse the impact of practice style or professional norms on variation, but few have analysed the two together. This might be because some of these factors are quite easily identified and are measurable, whilst others tend to be not easily measured or are unobservable to the researcher. In contrast to the usual approach, this study will use an estimation framework that enables the majority of these factors to be taken into account simultaneously, with a strong emphasis on the unobserved heterogeneity of both patients and providers. Andersen (2009) recognises the benefits of such an approach and suggests that integrating the ideas from different theories on physician behaviour can produce different and more complete results.

The estimation approach adopted in this study allows for a similar analysis to that provided by the multilevel approach, however complexities of the real world and in particular complexities in the health care system mean that the data is not always in strict hierarchies. It is often the case that individuals are likely to be in more than one unit of the higher level and over time move between units at the higher level. This is the case in the dataset that will be used here. The lower level units are patients and the higher level units are providers (dentists). The data consists of repeated observations on both dentists and patients, and patients move between dentists. Rather than adopt a multilevel approach, the empirical methods described in Chapter 3 provide a way to analyse variation with non-nested data in the presence of, and controlling for unobserved patient and dentist heterogeneity. A fixed effects framework provides consistent estimates of the variables in the model and allows for the separate identification of the unobserved patient and dentist heterogeneity.

2.5 Conclusion

There is little doubt about the existence of variation in health care. It has been well documented in the literature and shown to exist across all levels of the health care sector. Widespread variations raise questions about efficiency, equity and quality of care, at a time when health care costs continue to soar. There is a growing recognition among governments and health care professionals of the importance of being able to identify the sources of variation, and to be able to understand and measure it.

Variation in healthcare can be categorised under two main headings; variations in the utilisation of services (activity) and variations in health outcomes. Within these categories the causes or sources of the variation are different, with any attempts to reduce variation being dependent on its given source. Professor John Wennberg, the pioneer in the study of healthcare variation, identifies the sources of variation as being related to different types of care. For example, variation in the utilisation of services stems from variations in preference and supply-sensitive care, whilst the variation in health outcomes can most often be explained by variations in the use of effective care.

Studies of variation have moved on from the small area analyses that were dominant when Wennberg first began analysing variation. The literature reveals a range of determinants that may help to explain variation in health care and it is becoming widely recognised that factors influencing both the provider and the patients' behaviour can have an impact. Many of these factors will be observed and easily measurable, however many will not be observable. The result is a complex system of interactions, all of which to some extent contribute to the observed variation in health care utilisation and outcomes.

The aim of this study is to analyse the variation in the use of dental radiographs in Scotland. This will be considered in the context of the factors determining variation listed in section 2.4. The estimation approach and the level of analysis set this investigation apart from others. This study gives particular attention to measuring the contribution of *both* individual dentist and patient heterogeneity to the variation in the provision of dental radiographs.

Chapter 3: Empirical Methods

3.1 Introduction

Chapter 2 presented an overview of the literature on variations in health care and discussed a number of stylised facts about the types of variation that exist and its potential sources. It presented a brief discussion on the methods and empirical frameworks that have been applied in the context of health care, highlighting that the existence of variation across many levels in the health care sector is well documented. It became clear, however, that what are less well documented are empirical studies that actually aim to measure and quantify the variation arising from its different sources. This is a gap in the literature that this study will address by incorporating recent advances in micro-econometric modelling techniques into the analysis of variation in treatment decisions or outcomes, techniques that have mainly been used in the labour economics literature.

The chapter is not intended to provide a comprehensive review of all recent methods and modelling techniques that have been applied in the context of labour economics; it aims to provide the reader with information on relatively recent developments with regard to a specific type of data and corresponding econometric models, which have typically been applied to labour market studies. In fact, many of the methods described in the previous chapter (see section 2.4) are equally applicable to labour market analyses. The aim of this chapter is to discuss the origins and application of the particular models that will later be used in the empirical analysis of this study.

Section 3.2 describes the datasets in question, namely linked employer-employee data and discusses the rationale for and the creation of such datasets. Section 3.3 presents the general statistical model and discusses issues around identification and estimation. A practical solution to the estimation problem is given in section 3.4 by way of a fixed effects framework. Section 3.5 describes how such methods will be applied in the context of health care and provides a theoretical framework to motivate the empirical analysis in Chapter 5, and finally Section 3.6 concludes.

3.2 Linked Employer-Employee datasets

In the 1980s researchers in the field of labour economics recognised that the new types of data and econometric methods that were emerging would enable different types of research to be carried out; research that would be based on microdata and that could provide better answers to many questions concerning labour markets. Rosen (1986) described how *".... the greatest potential for further progress rests in developing more suitable sources of data on the nature of selection and matching between workers and firms....*" His attention focused on how such data could produce better estimates in the context of the theory of compensating wage differentials (or equalising differences) but also recognised its potential in other aspects of labour market analysis. Willis (1986) considered the role of better data in the context of the human capital model and the development of agency theories on the worker firm relationship. He recognised that, *".... future progress in this area will hinge crucially on the development of data which links information on the individual characteristics of workers and their households with data on the firms who employ them..."* There was wide recognition that there were some key elements missing in being able to fully understand firm performance and worker outcomes and at the same time the information gap required to do this was also recognised. This resulted in a number of years that saw the creation and development of *linked* employer-employee datasets.

In May 1998, The International Symposium of Linked Employer-Employee Data was held in Washington DC, with its main aim being to address the benefits and challenges of constructing and making use of such datasets. This conference brought together a number of statisticians and social scientists from around the world, representing 20 countries in all. It provided a unique opportunity for researchers to learn from each other and to demonstrate the value of research based on data that links worker *and* firm characteristics. It also facilitated a discussion around potential research that could provide international comparisons in this field.

The organisers of the event invited eight delegates to provide a summary of the papers presented in each session, which then later formed the basis of a Conference Report. (Haltiwanger et al. 1998) This report identified eight main themes that were presented and discussed during the two day conference and are listed as follows:

- Creating employer-employee datasets
- Confidentiality of linked data
- Econometric issues
- Analysing training and productivity
- Analysing firms, workers and wages
- Analysing firms, jobs and turnover
- Program development and policy analysis

- International comparisons

It became apparent from this group meeting that many other countries, particularly in Northern Europe, had made much more progress in constructing and using linked datasets, compared to the United States. Prior to 1998, worker-firm linked datasets had been used to analyse data in Canada, France, Scandinavia, Netherlands and Belgium.[6] At the time Sweden in particular had a large detailed dataset that linked information on workers and firms. It not only contained detailed information on many firm and demographic characteristics, but also had detailed accurate job classifications. Lazear & Oyer (2004) suggested that the lack of detailed job information was one of the weaknesses of the US datasets that were being constructed. The inclusion of such information enables the empirical researcher to answer many more questions relating to the internal workings of the firm and to better follow employees as they change jobs. This therefore provided a useful environment for lessons to be learned across countries and sparked the development of similar datasets in the US. One such example is the Linked Employer-Household Dynamics (LEHD) dataset, which was set up within the US Census Bureau. It uses modern statistical and computing techniques to combine federal and state administrative data on employers and employees with core Census Bureau censuses and surveys. Abowd et al. (2004) provide a description of the creation and contents of this dataset and set out plans for its future development.

In 1999, the same authors who provided the Conference report published the book, *The Creation and Analysis of Employer-Employee Matched Data*, (Haltiwanger et al. 1999). This book provides an in depth detail of all the papers

[6] See, for example, Krebs et al. (1999); Abowd et al. (1994); Hassink (1999); Audenrode (1999)

presented and discussed at the symposium. It divides the papers into sections that focus on the creation of matched employer-employee datasets, analyses using these datasets and any econometric issues involved with their use.

More recently, on 16th September 2005, the Department of Trade and Industry (DTI) and Policy Studies Institute (PSI) held a one day workshop in London that brought together some of the principal analysts of linked employer-employee data. The main aim of the conference was to address the ways in which linked employer-employee datasets can make a contribution to policy analysis, an area that DTI felt had received less attention in the literature. A detailed report on the workshop and the papers presented was published by Bryson et al. (2006).

Conferences like the two described above are not unique and many countries have held similar discussions (For example, Denmark, Finland, Germany, New Zealand and Austria). This highlights the interest and the importance that has been given to both the creation and the use of such datasets. They continue to be used extensively in the literature and continue to help advance the understanding of labour markets.

3.2.1 The Rationale for Linked Data

As discussed in the section above, in the 1980s and 90s there was wide recognition of the importance of developing datasets to assist in empirical research of labour markets. As the interest in the internal working of firms and organisation grew, it became clear that to fully answer many of the emerging questions it would be necessary to have data that *links* information on the individual characteristics of workers (and the households they belong) with data on the firms who employ them (Willis 1986). Matching the data on workers, to data on the firms in which they work, provided the empirical basis to revisit and refine some of the theories of the firm, for example, production, mobility and turnover of workers, industrial organisation and compensation design. In the years that followed the papers by Rosen and Willis, economists and social scientists in general made huge progress in creating and using matched employer-employee datasets. Abowd & Kramarz (1999a) documented two emerging themes:

- The importance of person *and* firm variables in the determination of compensation.
- The importance of *individual mobility* in relation to firm-specific employment adjustments.

They recognised that the matching of the data is what would allow more precise measurement of both personal and job attributes, both of which are required for empirical calculations.

Typically analyses of the variations in labour market outcomes, for example, wages, were conducted using cross sectional data taken from household surveys. These traditional surveys of workers contained many individual characteristics (such as education, age, gender, occupation) and in some cases firm characteristics too. They allowed for one level of variation in wages to be measured i.e. that due to individual characteristics. Although much can be learned from these studies, inference is often indirect and may suffer from inconsistent or inaccurate self-reported data (Lazear & Oyer 2004). By expanding the data to longitudinal datasets, this opens up the possibility of measuring the contribution to the observed total variation in earnings, of unobserved time-invariant individual characteristics (for example motivation, family characteristics). Adding the link to information on employers allows the separation of two more sources of variation, i.e. the proportions due to observed and unobserved employer characteristics. Abowd et al. (2004) noted the importance of these types of new measures in terms of explanatory power. They considered the case of analysing the impact of firm quality on worker outcomes as well as the impact of workforce quality on firm outcomes and found that analyses that rely on traditional cross sectional data can account for approximately 30% of earnings variation. However, analyses that exploit the linked nature of the data and obtain new measures of worker and firm quality, can account for close to 90% of observed variation in earnings. It became evident that linked employer-employee datasets would provide great research potential. They would enable many labour market issues to be analysed from both the demand and the supply side, where previously, research relied heavily on supply side factors. The conference report from the DTI workshop provided a succinct summary of the unique advantages of using linked employer-employee data and described the four ways in which such data can offer insights into processes within firms and in the labour market at large (Bryson et al, 2006). The four points are summarised as follows[7]:

- If there is something 'specific' to worker-firm matching which generates both costs and returns to both parties, then labour market dynamics can only be properly and fully understood by being able to observe that match.
- The inclusion of data from both the employer and the employee allows for features that would otherwise be unobserved to be included in analyses. This not only leads to enriched analyses, but also helps to overcome some of the

[7] For full details see *Making Linked Employer-Employee Data Relevant to Policy*, DTI Occasional Paper NO.4, 2006.

biases inherent in analyses that rely on data either solely on employers or employees.

- Multiple observations of employees within multiple workplaces permit analyses of labour market issues that are attributable to within- and across-workplace dispersion e.g. distribution of pay
- Longitudinal linked employer-employee data allow for a much more rigorous assessment of causal processes that might not otherwise be possible e.g. worker and employer selection processes

3.2.2 The Creation of Linked Datasets

The types of conferences described above, led to an explosion of interest in these datasets and how they could be applied in a research setting. The was a large increase in the number of empirical studies making use of matched datasets, in many different countries, though at the time not much in the literature about how to actually construct the data. The Washington conference provided a useful forum for discussions on this and the book that followed devoted a section to this very issue (See Section 3, Haltiwanger et al 1999). Abowd & Kramarz (1999a), in their chapter in the Handbook of Labor Economics, recognised that many economists would not actually be familiar with the methods used to construct matched employer-employer data and therefore provided a detailed discussion on how to do this and the types of issues involved. According to the authors, it is necessary to select the data sources appropriate for answering the questions under investigation. There are three different types of matching and two dimensions that distinguish the matched data. Data is matched by linking survey-survey, survey to administrative and administrative-administrative data. Some datasets are cross sectional in nature, others are longitudinal; and some frameworks focus on the employee, whilst others use the firm as the primary unit of analysis.

Abowd and Kramarz proposed that their chapter in the Handbook of Labor Economics (Chapter 40, 1999) could act as a reference for researchers using matched employer-employee data, to ensure they do choose the appropriate data sources. They go to great lengths to discuss the design of different types of data sets and divide them into categories according to their representativeness, for example representative cross section of firms with either representative or non-representative data on workers, representative cross section of workers matched with longitudinal data on firms, and representative matched worker-firm panels (from either administrative or statistical survey data).[8] The authors also directed attention to the fact that not all matched data were designed with the intention of creating representative data on the set of workers or firms within a given region or country, and numerous studies of labour markets are conducted using this type of data. (For examples see Groshen (1996) and Brown & Medoff (2003))

Jensen (2010) provides an up to date summary of the major matched employer-employee datasets that are currently in use around the world. This overview does not attempt to draw on any similarities or differences between the datasets, but merely sets out the broad characteristics of each and identifies some recent analyses that have been conducted using them. A few examples are provided below:

- *US Worker Establishment Characteristics Database* – This links data for a sample drawn from the 1990 Decennial Census of Population to employers'

[8] For a complete discussion refer to the Handbook of Labor Economics, Vol 3B, Chapter 40, pp2629-2710

data from the 1989 Longitudinal Research Database. For an application see Hellerstein & Neumark (2008).

- *French Linked Employer-Employee database* – Data are collated from four different sources: a longitudinal dataset of firms accounts, the Modification of Structure Database (contains all asset transfers between firms), the Annual Declarations of Social Data (longitudinal data on jobs held by every worker in France) and the Permanent Demographic Sample (other census based data on individuals). With such rich matched data, the French dataset has been used in a number of studies, for example, Abowd Kramarz and Margolis (1999), Goux & Maurin (2000), and Margolis (2006).
- *British Workplace Employee Relations Survey 1998* – This was the first example of a matched employer-employee dataset in Britain and included all workplaces with 10 or more employees across a range of industries. It was repeated in 2004 and contained information on more than 3000 managers and 20,000 employees. For an application see Frijters et al. (2003).

The paper by Jensen (2010) also provides information on datasets used in New Zealand, Japan, Canada, Denmark, Germany and Australia.

3.3 The General Statistical Model

This section draws heavily on Andrews et al. (2006). They describe the basic generic linear model that can be identified with matched employer-employee datasets. Note that this model is analogous to the general specification described by Abowd & Kramarz (1999a). The vast majority of the analyses conducted using such data use a variant of the model given by Equation (3.3.1) below:

$$y_{it} = \mathrm{x}_{it}\beta + \mathrm{w}_{jt}\gamma + \mathrm{u}_i\eta + \mathrm{q}_j\rho + \alpha_i + \phi_j + \mu_t + \epsilon_{it} \qquad \textbf{(3.3.1)}$$

where y_{it} is some measured outcome for the individual $i = 1, \dots., N$

workers are observed once per period $t = 1, \dots, T_i$ in firm $j = 1, \dots, J$ and can change firms over time

x_{it} and u_i are vectors of observable i-level covariates

w_{jt} and q_j are vectors of observable j-level covariates

It is assumed that workers will enter and exit the panel, resulting in an unbalanced panel with T_i observations per worker

There are $N^* = \sum_{i=1}^{N} T_i$ observations (worker-periods) in total.

The error components are α_i for the worker, $\phi_j$for the firm and the third component μ_t represents the unobserved time effect.

It is assumed that the error components (unobserved heterogeneities) can be correlated with each other and with any of the observable explanatory variables which means fixed effects estimation is required to estimate the parameters of (3.3.1).

ϵ_{it} is the stochastic disturbance term and is assumed to be strictly exogenous. This implies that worker's mobility decisions are independent of ϵ_{it}(a requirement for identification – see section 3.3.2.1 below).

Equation (3.3.1) contains all four possible types of covariate that may be of interest to researchers; α_i and u_i are time-invariant variables for workers, whilst x_{it} are variables that vary across individual workers and time. Similarly ϕ_j and q_j are variables that are fixed over time for firms, whilst w_{jt} vary across firms and over time. Fixed effects estimation of the general model would result in the parameter vector $[\eta, \rho]$ associated with the time-invariant variables not being identified. Rather than dropping $[\mathrm{u}_i \mathrm{q}_j]$, Andrews et al (2006) defines what Abowd & Kramarz (1999a) described as the pure person effect and pure firm effect. The pure person effect is given by:

$$\theta_i \equiv \alpha_i + \mathrm{u}_i \eta \qquad \textbf{(3.3.2)}$$

It combines the effects of observable time-invariant personal characteristics and unobserved personal heterogeneity. Similarly the pure firm effect is given by:

$$\psi_j \equiv \phi_j + \mathrm{q}_j \rho \qquad \textbf{(3.3.3)}$$

It combines the effects of observable time-invariant characteristics of the firm and unobservable firm heterogeneity. Hence equation (3.3.1) can be written as:

$$y_{it} = \mathrm{x}_{it}\beta + \mathrm{w}_{jt}\gamma + \theta_i + \psi_j + \epsilon_{it} \qquad \textbf{(3.3.4)}$$

and in matrix notation, is given by:

$$y = X\beta + W\gamma + D\theta + F\psi + \varepsilon \qquad \textbf{(3.3.5)}$$

where X is the $N^* \times K$ matrix of observable time-varying individual characteristics, W is the $N^* \times K$ matrix of observable time-varying firm characteristics, D is the $N^* \times N$ matrix of indicators for individual $i = 1, \dots, N$, F is the $N^* \times J$ matrix of indicators for the firm at which i works at date t (J firms in total), y is the $N \times 1$ vector of outcomes, ε is the vector of residuals, and $N^* = NT$.

The parameters of (3.3.5) are β, the vector of coefficients on the time-varying personal characteristics; γ, the vector of coefficients on time-varying firm characteristics; θ, the $N \times 1$ vector of individual effects; ψ, the $J \times 1$ vector of firm effects; and the error variance, σ_{ε}^{2}. The parameter θ includes both the unobservable individual effect and time-invariant personal characteristics, as does ψ include both the unobservable and time-invariant firm effects. Equations (3.3.1) and (3.3.5) are interpreted as the conditional expectation of individual outcomes given information on the observable characteristics, the identity of both the individual and the employing firm, and the time at which the observation occurred (Abowd & Kramarz, 1999a).

3.3.1 Interpretation Issues

Although the number of authors conducting analyses using linked employer-employee data grew rapidly in the 1990s and beyond, and many did estimate models similar to (3.3.5), in most cases the full model was not estimated. This led to considerable ambiguity about the precise interpretation of various combinations of the parameters of the model, which Abowd, Kramarz and Margolis (AKM hereafter, 1999) decided to address. In this paper, they described the importance of recognising that the omission or aggregation of one or more of the effects in (3.3.5) can change the meaning of the other effects significantly. Variations in the set of conditioning effects can lead to omitted-variable bias and the use of different linear combinations of the effects can lead to aggregation bias. Sometimes this can be in a very subtle way that is not always clear from the specific equation being estimated. AKM (1999) investigated each of these variations in turn in the context of different problems in the labour force, for example, inter-industry wage differentials, firm-size wage effects, and measuring internal and external wages.

To summarise, any analysis that estimates models (or variants) of the general form given by (3.3.5), will result in omitted variable bias, if either the person or firm effects are excluded from the analysis. When the estimated version of (3.3.5) excludes the pure firm effects, the estimated person effects, are the sum of the pure person effects, and the employment duration weighted average of the firm effects for the firms in which the worker was employed, conditional on the individual time-varying characteristics. Similarly, in the case of omitting the pure person effects from the estimated version of (3.3.5), this results in estimates of the firm effects that can be interpreted as the sum of the pure firm effects, plus the employment-duration weighted average of the person effects of all the firm's employees in the sample, conditional on the time-varying individual characteristics. The estimated coefficients on the time-varying characteristics in the case of either omitted firm or person effects will also be biased.

Prior to the work of AKM (1999), almost all of the analyses estimating equations like (3.3.5), produced estimated effects that confounded the pure person and pure firm effects, in the form of an omitted variable bias. The possibility of being able to *identify* both person and firm effects, therefore allowed researchers using matched employer-employee data to re-examine many important topics in labour economics using estimates that properly allocated the statistical effects associated with workers and firms. For example, Woodcock (2003) considers the role of heterogeneity and the worker firm match on wage dynamics and employment decisions. Abowd et al. (2003; 2005), also consider the worker firm match and examine whether 'good' workers are employed by 'good' firms. The 2005 paper re-visits one of the most debated issues in labour economics; inter-industry wage differentials. Dostie (2005) presents new evidence on returns to seniority using linked employer-employee data, looking particularly at the relation to worker turnover and Bryan (2007) uses matched Canadian data to examine the relationship between workers, workplaces and working time.

3.3.2 Identification and Estimation

Section 3.3 above presented the general specification of the statistical model underlying the majority of analyses making use of linked employer-employee data and discussed some issues around interpretation of the parameters. This section considers the identification of the model parameters and some early estimation methods.

3.3.2.1 Identification of Person and Firm Effects

Identification of the model requires repeated observations (on the same workers and the same firms) and mobility in the sample. Mobility is a necessary condition if one wants to separately identify person and firm effects in the general model. The separate identification of these effects requires the presence of individuals who move from firm to firm. Abowd and Kramarz (1999a), summarise this condition as follows, "*...The individual and firm effects are both identified whenever an individual that appears in the sample works for a firm that employs at least one individual, also in the sample, who moves to another firm, which, necessarily, also appears in the sample.*" (p. 2662) In order to highlight the complexities of identification in the model, it is useful to consider a very simple example. Suppose there are only 3 individuals/workers (1, 2, and 3), two firms (*A* and B) and two time periods ($t = 1, t = 2$). The necessary mobility condition required for all individual and firm effects to be identified can be shown by the following simple illustration:

Figure 3.1: Mobility Condition for Identification of Person and Firm Effects

	$t = 1$		$t = 2$
1	A		A
2	B		B
3	A	$\longrightarrow$	B

Individual 1 is continuously employed at firm A; individual 2 is continuously employed at firm B, and individual 3 moves from being employed at firm A in the first period to being employed at firm B in the second period. It is this movement of individual 3 that allows for all three individual effects to be identified and both firm effects to be identified. Consider the situation where individual 3 isn't mobile and stays employed at firm A, then firm B effect cannot be distinguished from individual 2 effect and individual 1 and 3 effects will be entirely within firm A effect[9].

Abowd, Creecy and Kramarz (ACK hereafter, 2002), expand on the identification issue further and demonstrate how the problem can be solved by applying methods from graph theory to determine groups of connected individuals and firms. Then, within a connected group of either individuals or firms, identification can be determined using conventional methods from the analysis of covariance. For individuals and firms to be connected, it is necessary that some individuals in the sample are employed at multiple firms. The authors state that,

[9] Both individual and firm effects are subject to the usual identification restriction that they sum to zero.

"When a group of persons and firms is connected, the group contains all the workers who ever worked for any of the firms in the group and all the firms at which any of the workers were ever employed."(p. 3)

A recent study from the economics of education literature (Kramarz et al. 2008) also considers mobility in the context of identifying their model. This paper uses data from the National Pupil Database (NPD), which is a comprehensive administrative register of all pupils in state schools in England, and applies similar estimation methods to that in AKM. The authors indicate that identification of the model specifications requires both *sufficient* and *exogenous* mobility.

3.3.2.2 Estimation of the Model

The requirements for identification of the model i.e. repeated observations on workers, repeated observations on firms and sufficient mobility in the sample means that extremely large datasets are needed. The creation of this type of dataset, although it solves the problem of identification, in doing so it creates a problem in terms of estimation. The full least squares solution to the estimation problem given by Equation (3.3.1) solves the normal equations for all estimable effects:

$$\begin{bmatrix} X'X & X'D & X'F \\ D'X & D'D & D'F \\ F'X & F'D & F'F \end{bmatrix} \begin{bmatrix} \beta \\ \theta \\ \psi \end{bmatrix} = \begin{bmatrix} X'y \\ D'y \\ F'y \end{bmatrix}$$

In typical applications, the cross product matrix on the left hand side of the equation is too high dimensional to solve using conventional algorithms, like those found in general linear modelling software such as SAS and Stata. This is because the memory requirement is too great for packages like this (which store all data in memory). Not only does the data matrix have to be stored, but also the created mean deviations for all observations. Consider the case of $N^* = 1.2\text{m}$; $J = 3000$; $K = 100$. The data matrix to be stored is $(K + J) \times (K + J)$; the data matrix for the J mean deviations is $N^*(K + J)$. Assuming that everything is stored in double precision (8b per cell), the data requirement would be 60 GB, which is far beyond the capacity of most computers available to researchers.

Initial analyses using linked employer-employee data could therefore not provide the full least squares solution. AKM showed that many common methods of approximating the solution can be derived by considering an augmented version of the equation. This is whereby ancillary effects defined in conjunction with interactions of observable characteristics of persons and firms are inserted into the model. The technique produces consistent estimates of the time-varying personal characteristics, firm effects and functions of person effects. Abowd, Finer and Kramarz (AFK hereafter, 1999) expand on the above by applying a technique that allows estimation of a large number of firm effects along with all of the person effects.

ACK (2002) provide new methods to obtain the exact solution to the estimation problem. The same data is used and the exact results fully confirm the results found in AFK, but give slightly different results found by AKM. It is believed that the explanation for the difference lies mainly in the limited capacity of the computers that were used in generating the approximations – hence the approximation in this instance was not sufficiently accurate. The output provides a non-unique set of effects to which the identification procedure is then applied. In order to make the effects unique for each group, one person effect is eliminated by setting the group mean person effect equal to zero. The overall mean person and firm effects are also set to zero. This then enables the grand mean of the dependent variable and a set of $N + J - G - 1$ person and firm effects to be identified. The effects will be measured as deviations from the grand mean of the dependent variable.

3.4 Practical Fixed Effects Estimation

Andrews et al (2006) propose a practical solution to the estimation problem and make the fixed effects methods described in AKM more accessible to the researcher by showing how they can be implemented in Stata. Matched datasets that are panel in nature can be thought of as having three dimensions of variation. This type of data are becoming increasingly available to researchers not only in the labour economics field, but in various other fields such as education and health, where the data may be on pupils in schools or patients in hospitals. These datasets are often referred to as multilevel or hierarchical. The approach by Andrews et al (2006) is slightly different to that applied in hierarchical models, as the data on workers, in this context, is not 'nested' within firms (as is often the case in these models).

The approach adopted is a familiar one though and they look to the econometrics literature on panel data methods, in particular the error components framework. Linear error components models are used frequently in the literature to analyse panel data and can take different forms, depending on how the errors are treated. In equation (3.2.1) the error component disturbances comprise α_i, the unobserved individual effect, ϕ_j, the unobserved firm effect, μ_t, the unobserved time effect and ϵ_{it}, the remainder stochastic disturbance term. Models with error structures such as this are referred to as three-way error components models. Central to the estimation of these models is the concept of random and fixed effects. Andrews et al (2006) proceed to develop methods for fixed effects estimation. This is due to the underlying assumption pertaining to the random effects models, in which it is assumed there is no correlation between the error components and any of the observed explanatory variables. It is highly likely that this will not be the case and so fixed effects estimation is used. The following sections provide a brief summary of the assumptions underlying the random and fixed effects models.

3.4.1 Fixed Effects Models

Consider the basic one-way error components structure where $u_{it} = \mu_i + \nu_{it}$. In the fixed effects case μ_i are assumed to be fixed parameters to be estimated and the remainder disturbances ν_{it} are independent and identically distributed IID (0, σ_ν^2). It is assumed that X_{it} are independent of the random error for all i and t, though can be correlated with μ_i. The fixed effects model is a suitable specification when the levels of an effect constitute the entire population of interest and inference is based only on this level. For example, the study could be on a specific set of firms or countries where inferences would be based only on this set of firms or countries. Any inference will be conditional on the particular firms or countries observed.

One way to estimate the fixed effects model is to use the 'within' transformation. This is a technique that uses a transformation matrix to 'sweep out' the individual effect μ_i so that individual observations are measured as deviations from individual means over time (time de-meaning). The transformed model can then be estimated using ordinary least squares (OLS). The within estimator for fixed effects cannot estimate the effect of any time-invariant variables, including the unobserved individual effect, as they are wiped out by the transformation. An alternative to this approach is to use the least squares dummy variable (LSDV) method (Baltagi 2001; Hsiao 2003). In this case the time-invariant variables are substituted with dummy variables and the model can be estimated using OLS. An advantage of this method is that it is possible to recover estimates of the individual effects. The downside, however comes when N (firms, schools etc.) is large. The model relies on including dummy variables ($N-1$), this is $N-1$ extra parameters to be estimated and opens up the possibility of multicollinearity among the explanatory variables.

3.4.2 Random Effects Models

Random effects models treat μ_i as a random variable. In this case $\mu_i \sim$IID (0, σ_μ^2), $\nu_{it} \sim$IID (0, σ_ν^2), and μ_i are independent of the ν_{it}. It is also assumed that the individual effects are uncorrelated with all explanatory variables, for all i and t. Random effects models are appropriate when making inferences on an entire population and usually the components being analysed represent only a sample from that population. For example, analysis could be on N individuals randomly selected from a large household survey.

Estimation of the random effects model uses the generalised least squares (GLS) method. This is a transformation that removes any serial correlation in the error term, i.e. between μ_i and ν_{it}. The transformed data can then be estimated using OLS. An advantage of the random effects model over the fixed effects model is that the data is only partially demeaned and therefore it is possible to obtain estimates of the effects of any time-invariant variables.

3.4.3 Spell Fixed Effects

Baltagi (2005) shows that algebraic solutions are available for the estimation of all parameters in a two-way error components model, however in the case of data with higher ordered dimensions there is no algebraic transformation which can sweep away all the fixed error components in one go and which allows for them to be recovered. Many of the linked employer-employee datasets described in Abowd and Kramarz (1999a) and Jensen (2010) are panel in nature and therefore have three dimensions of variation i.e. across workers, firms and time. They can therefore be considered in a three-way error components framework. Andrews et al (2006) estimate equations of the form given by (3.3.4). Note that the unobserved time effect μ_t does not appear in this equation. It is assumed to be fixed and estimated directly using time dummies, which are subsumed into one of the vectors of observable covariates. This means that essentially they are analysing a two-way error components model. A number of ways to estimate the parameters of (3.3.4) using fixed effects methods are described, two of which are considered here. The first method is referred to as spell fixed effects.

Spell fixed effects is a useful method for estimating (3.3.4) if the only requirement is to obtain consistent estimates of β and γ. It is a relatively straightforward method that relies on the fact that θ_i and ψ_j do not vary for each 'spell' of a worker within a firm. Spell level heterogeneity is defined as $\lambda_s \equiv \theta_i + \psi_j$ to give:

$$y_{it} = \mathrm{x}_{it}\beta + \mathrm{w}_{jt}\gamma + \lambda_s + \epsilon_{it} \tag{3.4.1}$$

The data is then transformed by subtracting averages at the spell level:

$$y_{it} - \bar{y}_s = (\mathrm{x}_{it} - \bar{\mathrm{x}}_s)\beta + (\mathrm{w}_{jt} - \bar{\mathrm{w}}_s)\gamma + (\epsilon_{it} - \bar{\epsilon}_s) \qquad \textbf{(3.4.2)}$$

The effects of the time-invariant variables for worker and firm, u_i and q_j are not identified and any variable x_{it} or w_{jt} that is constant within a spell will also not be identified. This is a practical and simple solution that can easily be implemented in Stata using the xtreg, fe command. The downside to this method is that not only are the time-invariant variables not identified, but it is not possible to separately identify the worker and firm heterogeneities either.

3.4.4 Least Squares Dummy Variable (LSDV)

If it is important to recover estimates of θ_i and ψ_j, or of ρ and η using equations (3.3.2) and (3.3.3), an alternative is the least squares dummy variable method, mentioned in section 3.4.1 above. However, as discussed, direct estimation of (3.3.4) using dummy variables when the dataset is large is not usually computationally feasible. In this model there are $K + N + J$ parameters to be estimated. In the case of a two-way fixed effects model, this problem is overcome by using the within transformation which sweeps out the i-level heterogeneity. However in the case of the three-way model with both i and j-level heterogeneity, there is no algebraic transformation of the observables that sweeps out both heterogeneities *and* which allows them to be recovered. One way to overcome this problem, is to include dummies for the firm heterogeneity, but sweep out the worker heterogeneity algebraically using the within transformation. AKM noted that this method gives exactly the same solution as the LSDV estimator.[10]

[10] In linear models, there is no distinction between removing the heterogeneity algebraically or adding two full sets of dummy variables, for workers and firms, and so the terminology LSDV applies to both.

A dummy variable must be generated for each firm:

$$F_{it}^{j} = 1(J(i,t) = j) \quad j = 1, \dots, J$$

where $1(J(i,t) = j)$ is the dummy variable indicator function and $J(i,t) = j$ maps worker i at time t to firm j. Substitute

$$\psi_{J(i,t)} = \sum_{j=1}^{J} \psi_j F_{it}^{j}$$

into equation (3.3.4) and time demean over i:

$$y_{it} - \bar{y}_i = (\mathrm{x}_{it} - \bar{\mathrm{x}}_i)\beta + (\mathrm{w}_{jt} - \bar{\mathrm{w}}_i)\gamma + \textstyle\sum_{j=1}^{J} \psi_j (F_{it}^{j} - \bar{F}_i^{j}) + \epsilon_{it} \qquad \textbf{(3.4.3)}$$

Andrews et al (2006) label this estimator *FEiLSDVj* to distinguish it from the full dummy variable estimator LSDV. The two estimators are actually identical, just different in the way they are computed. As discussed in section 3.3.2.1, identification of the firm effects is dependent on mobility. $F_{it}^{j} - \bar{F}_i^{j}$ will be zero for all J dummies for any worker who does not change firm and will only be non-zero for workers who change from one firm in the sample to another firm in the sample. Identification of ψ_J is driven by the total number of such movers in each firm.

Once estimates of (β, γ) have been made, it is possible to recover estimates of the error components $\theta_i$and ψ_j. First compute

$$\hat{\psi}_{J(i,t)} = \textstyle\sum_{j=1}^{J} \hat{\psi}_j F_{it}^{j} \qquad \textbf{(3.4.4)}$$

and then

$$\hat{\theta}_i = \bar{y}_i - \bar{\hat{\psi}}_i - \bar{\mathrm{x}}_i\hat{\beta} - \bar{w}_i\hat{\gamma} \qquad \textbf{(3.4.5)}$$

where $\bar{\bar{\hat{\psi}}}_i$ averages $\hat{\psi}_{J(i,t)}$ over t for each i.

Identification of firm effects is only possible within a 'group' as discussed in section 3.3.2.1 above and it is not possible to compare firm effects across groups. This is because it is arbitrary which ψ_j is set equal to zero for normalisation in each group. The same is true for the case of the worker effects θ_i. ACK suggested normalising estimates of $\psi_j$so they have the same mean across groups; Andrews et al adopt the same approach. They also discuss how to identify the effects of the time-invariant variables $\hat{\alpha}_i$ and $\hat{\phi}_j$ by estimating equations (3.3.2) and (3.3.3). It is then possible to analyse the distributions of the individual firm effects and worker effects, specifically to see if they are correlated. (See Andrews et al 2006, Section 3.4)

There are two potential computational problems with the FEiLSDVj estimator. The first, as in the case of LSDV, is when the number of firms J is large. Identification of the model relies on repeated observations on employees and employers. There also has to be sufficient mobility in the sample. With a large number of firms, the data requirements become extremely demanding. Software packages hoping to run this model will need to invert a matrix of dimension$(K + J) \times (K + J)$. The second issue is that J mean-deviations for N^*observations have to be created and stored. In statistical packages such as Stata, all data is stored in memory so when the number of firms is large it may not be feasible to estimate the model using FEiLSDVj.

Cornelissen (2008a; 2008b) presented a memory saving way to estimate the three-way error components model described above and constructed the Stata module felsdvreg to do so. A simple illustration can be used to highlight the computational problems that may arise when trying to estimate the model when the number of panel units is high. Consider a linked employer-employee dataset with J = 10,000, N^* = 20 million person-years, K = 50 time-varying regressors and 4 bytes of memory is required per data cell. Cornelissen (2008b) showed that for the transformed model $\tilde{y} = \tilde{X}\beta + \tilde{F}\psi + \tilde{\epsilon}$, the following memory would be required to store the data.

Table 3.1: Data Storage Requirements

Matrix	Dimension	Storage requirement
$(\tilde{X}, \tilde{F})$	$N^* \times (K + J)$	800 GB
$(\tilde{X}, \tilde{F})'(\tilde{X}, \tilde{F})$	$(K + J) \times (K + J)$	0.4 GB

Table 3.1 shows that the memory requirement for the cross product matrix is much smaller than for $(\tilde{X}, \tilde{F})$.

The system of normal equations to solve the model is:

$$A \begin{pmatrix} \hat{\beta} \\ \hat{\psi} \end{pmatrix} = B$$

with

$$A = (\tilde{X}, \tilde{F})'(\tilde{X}, \tilde{F})$$

$$B = (\tilde{X}, \tilde{X})'\tilde{y}$$

The solution to the problem lies in the fact that each element of A and B is a cross product sum of no more than two regressors. This means that only 2 regressors need to be stored in memory to compute one element of A and B. The X-part of the design matrix is provided as a dataset, whereas the F-part of the cross product matrix can be created during the estimation process without actually generating the F-part of the design matrix. The main idea behind the method is that only certain parts of the F matrix need to be created so time and memory can be saved. Full details of the decomposition used are given in Cornelissen (section 4, 2008a). The decomposition uses the fact that the F matrix is a sparse matrix i.e. parts of it are null sub-matrices which deliver no contribution to A or B and uses information on which firm a given worker is employed, which means only those elements of A and B that the worker contributes to have to be computed. For example, for workers who don't move between firms the firm dummy variables will be zero. Even for some movers the cross product matrices will be zero because the workers are employed in very few firms. Any zero elements of the sparse matrices involved are dropped from the computations.

The Stata program felsdvreg implements the ideas discussed above and produces results that are exactly the same as FEiLSDVj, so in other words it provides the full least squares solution that was missing in AKM (1999). It also analyses the structure of the dataset and produces some summary information on the number of movers and stayers and the number of firms workers have been employed in. This is important information for assessing the precision of the estimates. The precision of the firm fixed effects is a function of the number of workers who move between firms. The greater the mobility in the sample, the more precise the estimates will be. A decomposition of the variance is also provided at the end of the output. This provides an indication of how strongly each of the components (observed time-varying, firm effects, person effects and the residual) contributes to explaining the variance of the dependent variable. The time and memory saving aspect of this method makes it an attractive option for analysing fixed effects three-way error components models, as will be shown by the empirical analysis in Chapter 5.

3.5 Application in Health Economics

The sections above discuss the development and use of integrated data; focusing mainly on linked employer-employee datasets, though many of the authors also point out that these particular methods could be adapted to most other fields in economics; education and health are often quoted as examples. As discussed the key to the recent developments in labour market analyses was the availability of suitably linked datasets. Hence the key to any crossover of the methods described above also depends on the availability of suitable datasets in these other fields of economics.

Abowd, Kramarz & Roux (2006), in particular show that the techniques they use in the analysis of wages, mobility and firm performance can have broad applicability and consider health economics as an example. Consider first the labour economics framework. In this context ‘jobs’ are a key component, where a job consists of an association between an individual (worker) and an employing entity (firm). The linked datasets are constructed by following jobs over time and by adding information from other sources on workers and firms. This information on workers and firms is also longitudinal in nature and is integrated into the information on jobs (referred to as the job frame in Abowd et al 2006). Any analysis can then be conducted by using samples based on individuals, employers or jobs, depending on the empirical question being investigated. Successful integration of datasets depends upon the records in the job frame containing a unique individual and firm identifier, which must also be used in the other data sources with information on individuals and employers. It is the unique identifiers that enable the 'match' between worker and firm to be identified.

3.5.1 Data Requirements

Now consider a similar framework applied to a health care setting. In this context there are for example, patients and hospitals. Abowd et al. (2008) describe a 'job' in this framework as being the inpatient spell of a particular patient in a given hospital. To create the types of integrated datasets described above, it would then be necessary to have data relating to patients and also data relating to hospitals. This data would have to be integrated with the data that relates to the inpatient spell of the patient in a given hospital. Then it would be possible to analyse a sample of patients over time as they are treated in different hospitals. There are many interactions between patients and health care providers (patient and GP, patient and hospital doctor) and between health care providers and health care establishments (primary and secondary care) that these techniques described above could be applied to. For some of the examples given here, particularly for analyses that exhibit variation at three levels and would require estimation by the three-way error components model, in practice the data requirement often does not match the data availability.

Consider the example of analysing patients in hospitals over time. In order to separately identify patient and hospital effects there would have to be repeated observations on patients, repeated observations on the hospitals they are treated in and there would have to be information on patients being treated at different hospitals. In reality, situations like this are very uncommon, verging on the non-existent in the context of hospital care. It is unlikely there would be enough data collected on patients receiving treatment (the same treatment) in different hospitals.

Primary care data may provide a better framework as it might be more feasible to have repeated data on patients and repeated data on GPs, so it could be possible to ask the questions, is it individual GP effects or is it practice effects that lead to a particular treatment outcome. This type of analysis would require information on patients over time, information on GPs over time and instances when GPs change practice. It becomes clear that in the health care context, although the amount of health care data collected is huge, it may be the linking of appropriate datasets or the instances that certain actions occur (for example how often are patients treated in different hospitals or how often do patients change their GP) that make analyses like the ones described above not possible. It is, however, also clear that the collecting of such data and the subsequent creation of linked integrated datasets in health care will enhance the analyses that can be carried out and can provide better answers to many questions in the field, as was discovered in the labour economics literature.

The benefits of linked datasets have been recognised in the field of healthcare for many years. In the UK, the Oxford Record Linkage Study led the way, with work beginning in the 1960s (Acheson 1964; Acheson & Evans 1964). In Scotland, a similar programme started and has continued to grow and develop (Kendrick & Clarke 1993). In the beginning many ad hoc linkages were completed for epidemiological purposes, but since 1989 the creation of permanently linked national datasets has been underway, with a view to creating a sophisticated system that can benefit health services research (see for example the work of the Medical Record Linkage Team at ISD Scotland)[11]. Brameld et al. (2003) identified six comprehensive population based medical record linkage systems around the world

[11] Full details can be found at http://www.isdscotland.org/Products-and-Services/Medical-Record-Linkage/

that routinely link health administrative data. These included the Oxford and Scottish studies, but also systems from the US, Canada and Western Australia.

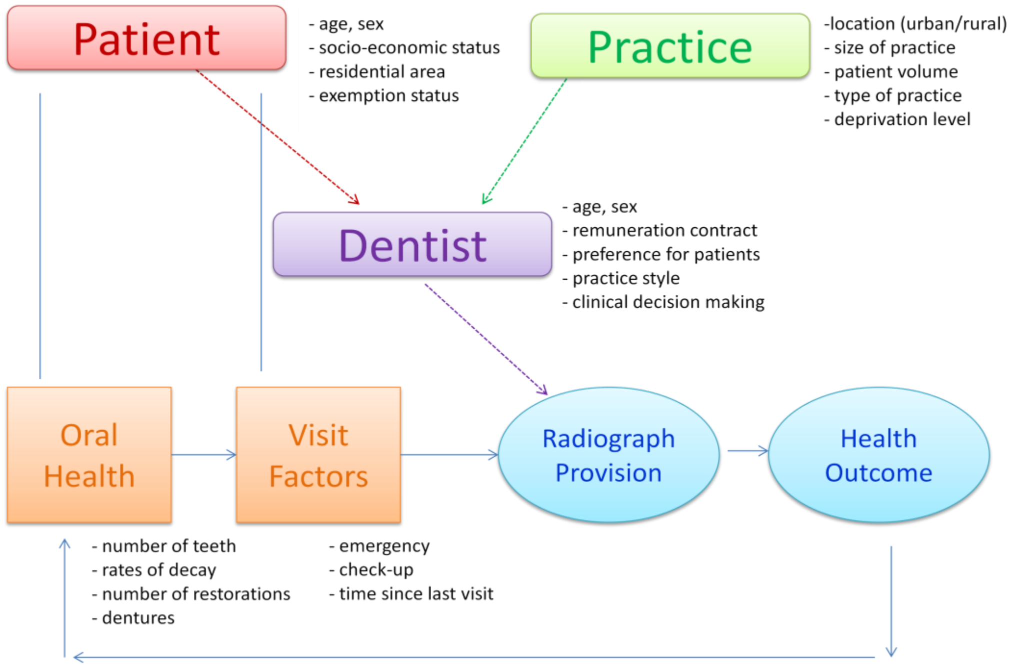
The Scottish dental data that is used in this study has many of the features necessary to carry out a three-way fixed effects analysis on the variation in the use of dental radiographs. It is not a panel dataset as such in that it does not contain information collected at specific points in time. It does however contain repeated observations on patients, repeated observations on dentists and there is mobility in the sample, i.e. there are a number of patients that change dentist over the sample period. It is also true that patients receive similar treatment from different dentists. Patients and dentists are characterised by unique identifiers which allows for the possibility of tracking patients and dentists over time. This means that using the three-way error components framework it is possible to fully analyse the variation in the provision of dental radiographs, in terms of considering both demand and supply factors, and more importantly in terms of observed and unobserved effects. This estimation framework will enable the contributions of the unobserved individual patient *and* the unobserved individual dentist, to the overall observed variation to be not only controlled for but also measured. An analysis of the variation in dental radiographs that makes use of this estimation framework is the first of its kind in the field of health economics, and in fact the use of this method in general in the health economics literature is not yet routine.

3.5.2 Theoretical Framework

The proposed estimation framework described above allows for the analysis of all possible covariates that a researcher might be interested in with regards to measuring variation. These include both time variant and time invariant factors for both dentists and patients. Although, to my knowledge, there are no studies that consider the variation in the provision of dental services (and more specifically radiographs) in this way, there have been some studies in the field of dental service provision that have attempted to explain the variation in service patterns by modelling the potential influencing factors separately or have included only a limited subset (Grembowski et al. 1991; Bader & Shugars 2007).

Brennan & Spencer (2005) recognised that more comprehensive models of the service provision process are required to improve our understanding of what is driving the pattern of care delivered. They developed a simple schematic model (see Brennan & Spencer, p182) to illustrate the complexity of the dental service provision process and the range of different factors involved. Figure 3.2 below presents a modified version of the model which has been adapted to reflect the provision of dental radiographs. It identifies that there are potentially patient, dentist and practice factors that impact on the decision to provide a radiograph. It is likely that dentists (given their individual characteristics) make their decisions about radiograph provision by taking patient and practice factors into account. Factors relating to the patient oral health and the type of visit, combined with the patient demographic factors may all impact on the dentist's decision to offer a radiograph. In order to decide what variables should be included in the empirical analysis, it is useful to summarise the factors that are likely to be taken into account on whether a radiograph is provided.

Figure 3.2: Schematic Model of Dental Radiograph Provision Process



3.5.2.1 Patient Characteristics

The first and possibly most important factor to be taken into account when the decision to provide a radiograph is taken is whether the patient actually needs one or not. Dentists use radiographs primarily as a diagnostic tool to determine the prevalence of common dental pathologies, with dental caries (decay) possibly being the most obvious one. They are also used to help identify dental calculus and to demonstrate/investigate periodontal bone loss. The decision to provide a radiograph will therefore be very much dependent on the underlying oral health of the patient. It will be related to the dental history of the patient, particularly in terms of rates of decay, numbers of restorations and even numbers/positions of teeth (anecdotal evidence suggests that radiographs are more often provided when there is overcrowding or poor positioning of teeth in the mouth).

Demographic and socioeconomic factors specific to a patient will also impact on the decision to provide a radiograph. These are factors such as the age of the patient and whether or not they pay for their treatment. Whether a person pays for their treatment or not is not only dependent on income levels but also other factors such as if the patient was pregnant or a nursing mother. A dentist will be aware of/consider these when making the decision about whether to provide the radiograph or not. Time factors may also play a role in the decision to provide a radiograph or not, for example, if a patient hasn't been to the dentist for a long time, are they more likely to be given radiographs at their next visit? Figure 3.2 above indicated that the type of visit is another characteristic that may influence the decision to provide a radiograph. Routine check-ups, new patients and emergency appointments are examples of types of visits which may provoke different responses from the dentist regarding the decision to obtain a radiograph.

Another group or class of patient characteristics that may be taken into account in the treatment decision are individual patient preferences. In general these are characteristics that are not observable and therefore difficult to measure. It might be the case, however, that although these preferences are unobservable to the researcher they very well may be observable to the dentist. Dentists are likely to get to know their patients over time and build up an understanding of their preferences. For example, if a patient has a strong aversion to receiving radiographs, it is likely that a dentist will know this. Similarly, some patients might have worries about the consequences associated with not providing a radiograph when one should have been provided and therefore become more involved in the decision making process. Again a dentist may be able to observe these characteristics over time. Even, the less well informed dentist, for example, when treating a new patient, can begin to learn this type of information by perhaps offering a radiograph at the first visit, again highlighting how the dentist uses the information about patients to inform their treatment decision.

3.5.2.2 Practice Characteristics

Characteristics specific to the dental practice may also influence the treatment decision. For example, the size, busyness, patient volume and location of the practice may all have a role in the decision making process. As with the case of the patient characteristics, the dentist can observe and is aware of these factors and may incorporate them into the decision to provide a radiograph or not. A busy waiting room may mean that there are time constraints, or in other words dentists face a higher opportunity cost of giving a radiograph, and so a dentist may decide not to do the radiograph; choosing to either do them at the next visit, or continuing a treatment plan without them.

Quite often dental practices in high deprivation areas automatically place most of their patients at high risk for dental caries. This practice characteristic could imply that dentists in these practices either don’t provide radiographs because they already expect a given level of caries, or alternatively, could provide more radiographs to patients because of the belief that patients are at high risk of developing problems.

3.5.2.3 Dentist Characteristics

From Figure 3.2 and the discussion above, it is clear that dentists use the information available on patients and their practice to inform the decision of whether to provide a radiograph or not. The dentist themselves also have certain characteristics that are potentially important in making the treatment decision.

Dentists will most likely first determine the clinical need for a radiograph to be provided. In doing so individual dentist specific characteristics may be important. For example, dentists may have varying beliefs and or knowledge about the diagnostic value of radiographs, some may find them particularly useful and are aware of their diagnostic properties so will provide them, whilst others may not.

The age of the dentist, which could imply level of experience, may be another factor in determining whether a radiograph will be provided. It might be the case that a dentist instinctively knows if there is a problem or not and doesn't require the diagnostic radiograph. Perhaps it is the case that there is no real level of uncertainty surrounding the provision of radiographs and the circumstances in which they are required. Physicians have been shown to be creatures of habit in making medical choices, and are slow to adopt new practices and technologies (Institute of Medicine, 2001). Is it the case that dentists also exhibit this habitual nature and tend to just stick to providing treatment (or not) in a given way. These factors relating to habits, knowledge and understanding of the benefits of radiographs as a diagnostic tool are all incorporated into 'practice style' effects. Wennberg (2002) and others (Wennberg et al. 1982; Eisenberg 1985) proposed that these practice style effects particularly manifest when professional uncertainty exists. Is this the case in relation to dental radiographs?

Training and skills may also be a factor that influences the decision to provide a radiograph. Some dentists may not have had much training and therefore have not acquired the appropriate skills to carry out the procedure so we might expect the numbers of radiographs provided to be increasing in the level of training acquired. Cost constraints at the dentist level may also influence the treatment decision. This may be linked to the remuneration contract under which the dentist is providing services. In Scotland dentists can be self-employed independent contractors, or paid by Health Boards on a fixed salary basis. Standard agency theory predicts that at least to some degree, health care providers are characterised by opportunistic behaviours motivated by financial gains (McGuire 2000). Thus, the fee-for-service payment structure may motivate dentists to influence the quantity of services that are provided. It might also be the case that this quantity differs from that of what a perfectly informed patient would wish.

For a fee-for-service contract dentist the opportunity cost in providing a radiograph is also likely to depend on if there are other possible treatments they could be doing that would be more valuable to them. Dentists may also be concerned about the consequences of mistreatment by not providing a radiograph. The result could be that a patient develops problems in the future and requires more extensive treatment. Dentists with these concerns may typically provide more radiographs to mitigate the risk of mistreatment and the potential damage to the dentist/patient relationship.

3.5.2.4 Theoretical Model

The discussion above highlights the complexity of the treatment decision and shows that many factors can influence the decision to provide a radiograph or not. It is assumed that dentists, with a given set of characteristics and preferences, use the information they have on their patients and practice to make the decision. Like in any physician/patient relationship the dentist and patient are jointly determining the treatment that is provided. To help understand this relationship further and to motivate the empirical analysis in Chapter 5, we can draw on principal agency theory and agency models.[12]

In their most basic form, principal-agent models are concerned with contracting relationships and the optimal compensation rules between an ill informed principal and an informed agent. These models have been applied in many different settings within the field of economics, but regardless of the context, the common theme is to provide optimal contracts in the presence of information asymmetry and uncertainty. In this context, patients (principals) enter into a contractual relationship with their dentist (agents). The information asymmetry that exists between the dentist and patient suggests that the dentist will have more influence in the treatment decision process. Principal agent models have been used extensively in the health care sector to analyse the impact of incentives that are inherent in the contractual arrangements of health care providers.

Another strand of the literature suggests that there are features of the health care market that can either mitigate or enhance the opportunistic behaviour provided by the payment system in the presence of information asymmetry (Chalkley & Malcomson 2000). For example in the presence of insurance, there is an incentive to exploit this behaviour even further, when physicians have an incentive to increase the volume of care provided until it leads to inappropriate levels of care (Barigozzi & Levaggi 2008).

Following the principles set out in Dranove (1988), which explores these factors relating to physician induced demand and the physician/patient relationship, a

[12] For a detailed discussion on principal-agent theory refer to Laffont & Martimort (2002)

simple theoretical model is derived to motivate the empirical analysis. Consider first the patient and the demand side:

Demand (Patients)

Just as health care can be considered an economic good where the demand is derived from the demand for good health (Grossman 1972), dental treatment can be thought of as an economic good derived from the demand for good oral health.

Let $u\big(X, h(y)\big)$ be a patient's utility defined in terms of a composite of all other goods X and oral health (h) which is a function of dental treatment (y) – and in this case a specific dental treatment, i.e. radiographs. The patient maximises utility subject to a budget constraint; $pX + p_y y = M$

and the usual first order conditions imply that X and h will satisfy:

$$\frac{u_X}{p} = \frac{u_h h'}{p_y} \leftrightarrow p_y u_X = p u_h h'$$

$$pX + p_y y = M$$

Patients can be exempt from charges which represents a situation of full insurance, where $p_y = 0$ is possible[13]. In a normal model of demand with non-satiation, zero prices mean infinite demand but health care, and also particularly relevant for dental treatment, does not always have to be utility enhancing. It is likely that even a moderately informed patient would not demand lots of radiographs.

Demand for a health care intervention (in this case radiographs) depends on its price, the general price level, income and patient characteristics/preferences embedded in $u(.)$, so for patient i, $u_i(X, h(y))$. Summarise the model by a

[13] Even though p_y is zero there may still be an opportunity cost of receiving a radiograph

radiograph demand function for patients such as $y^*_{pt}(p_y, p, M, i)$. We might expect demand to be increasing in the degree of insurance. Pauly (1986) describes the moral hazard problem and indicates that health insurance has the effect of reducing the price of treatment that the patient faces and leads to excessive demand because typically p_y will be less than the opportunity cost of resources required to produce the treatment. However, it is important to remember that in the presence of information asymmetry, where the patient is less well informed about their clinical need for a radiograph, this might not be the case.

Supply (Dentists)

The supply side is based on the ideas of physician agency. Consider a dentist choosing the number of radiographs y to perform on a particular patient. His costs $c(y)$ increase in y but he also places a value $b(y)$ on the treatment. In general terms the dentist will also face a payment function $P(y)$. For a salaried dentist this will just be a constant. The dentist will choose y to satisfy the first order condition $P_y + b_y - c_y = 0$. It follows that the dentist's supply of the treatment will be a function of the payment system, their preferences and cost and benefit functions. If we index these functions j to reflect the individual elements to give a supply function for the dentist of $y^*_d(P, j)$. We would expect the supply of dental radiographs to be increasing in the fee for radiographs.

Equilibrium

We have indicated that the decision on treatment is a joint one between the dentist and the patient. What would happen if the dentist and patient choices didn't match? In a conventional market setting, equilibrium would satisfy

$$y^* = \min[y^*_{pt}(p_y, p, M, i)], y^*_d(P, j)]$$

This implies that sometimes we would observe dentist characteristics entering, sometimes patient characteristics, but seldom both together. If the interaction really is one of physician agency alone, then $y^* = y^*_d(P, j)$. Only dentist characteristics and remuneration contract would matter. If there is some degree of bargaining/joint decision between the dentist and patient (dentists can most likely 'persuade' the patient though it may require some effort) then there would be some averaging of $y^*_{pt}(p_y, p, M, i)$ and $y^*_d(P, j)$ thus both patient and dentist characteristics and also patient insurance (exemption) and dentist remuneration is likely to affect the observed treatment.

Given the complexity of the dentist/patient interaction and the number of factors that are likely to impact on the treatment decision, it is difficult to find a suitable theoretical construct that can account for all this. The simple model presented above indicates how we would want to account for these factors but does not provide a model of all interactions. It does provide a basis though for the empirical estimation strategy that is adopted in this study and discussed in more detail in the section below.

3.5.3 Model Specification

This section presents the general model specification that will be used in the empirical analysis in Chapter 5. It relies heavily on the general specification used by Andrews et al (2006) and presented in section (3.3.1), only adapted for the Scottish dental data and to include an interaction term:

$$y_{ik} = \mu + \mathrm{x}_{ik}\beta + \mathrm{u}_{J(i,k)k}\gamma + \mathrm{w}_{ik}\eta + \mathrm{z}_{J(i,k)k}\rho + \delta\left(\mathrm{w}_{ik}.\mathrm{z}_{J(i,k)k}\right) + U_{ik} \quad \textbf{(3.5.1)}$$

where

$$U_{ik} = \alpha_i + \phi_{J(i,k)} + \varepsilon_{ik}$$

Patients are indexed $i = 1, \dots, N$

They are observed once per course of treatment (CoT) $k = 1, \dots, K$ provided by dentist $j = 1, \dots, J$

Patients can receive treatment from different dentists and the function *J*(*i*,*k)* maps patient *i* to dentist *j* for CoT *k*

y_{ik} is the probability of patient i receiving a radiograph on their *k*th course of treatment

x_{ik} is a set of observable explanatory variables that vary across patients and the patients different courses of treatment

$\mathrm{u}_{J(i,k)k}$ is a set of observable explanatory variables that vary across dentists and different courses of treatment

$\mathrm{z}_{J(i,k)k}$ is the remuneration contract of the dentist

w_{ik} is the exemption status of the patient

$\mathrm{w}_{ik}.\mathrm{z}_{J(i,k)k}$ represents the interaction between the dentist contract and exemption status

α_i is the unobserved patient specific effect

$\phi_{J(i,k)}$ is the unobserved dentist specific effect

ε_{ik} is the usual stochastic disturbance term.

The mapping function $J(i,k)$ is used because patients can be seen by different dentists. If Equation 3.5.1 above represents the probability that patient i will receive a radiograph in a given course of treatment k, the mapping function then tells us which dentist is providing the treatment, so we can think of y_{ik} as being the probability that patient i will receive a radiograph from dentist j in course of treatment k. Similarly, for the set of observable explanatory variables $\mathrm{u}_{J(i,k)k}$ that vary across dentists and course of treatment, the mapping function just identifies the particular dentist. Andrews et al. (2006) did not use the mapping function to subscript the equation, instead preferred to use j only. When this model specification is re-visited in the empirical analysis in Chapter 5, a similar approach is adopted.

Equation 3.5.1 is the general specification for the particular models to be estimated in the empirical analysis. The structure of the data enables the three-way fixed effects estimation described by Andrews et al (2006) to be applied and implemented using the felsdvreg Stata program constructed by Cornelissen (2008a).

3.6 Conclusion

Empirical studies that assess variation in health care often fail to produce satisfactory measurements of the actual contributions from different sources. This may be due to the fact that to actually achieve this, it requires a large amount of suitable data, with a particular structure, and estimation methods that can model the data in the correct way. This chapter presents an empirical framework from which this can be achieved and shows the types of datasets that are required. Much of the information has been borrowed from the field of labour economics where this type of framework has been developing over many years. It makes use of recent advances in micro-econometric modelling techniques and demonstrates how using such methods can lead to a better analysis of the variation in treatment decisions and/or outcomes in the field of health economics, by being able to control for *and* measure unobserved individual patient heterogeneity and unobserved individual provider heterogeneity at the *same* time.

The 1980s and 90s was a period where, in the field of labour economics there was much discussion around data, and the lack of suitable data required to fully answer some of the emerging questions on labour markets. There became widespread recognition that data relating characteristics of firms to characteristics of their workers would allow researchers to begin to disentangle the effects of firm level decisions from the effects of choices made by workers (for example, see Rosen (1986) and Willis (1986)). As Abowd & Kramarz (1999b) pointed out, *"...two of the most pervasive and difficult to explain phenomena in economics are the persistence of inter-industry and firm-size wage differences".* Some explanations predicted that most of the variation was due to the persons employed in the industry, whilst others predicted that the variation lies in the fact that firms or industries have different compensation policies. It was clear that the ability to be able to distinguish between the two explanations would require data from both sides of the market.

This led to an explosion of interest around the creation and use of linked employer-employee datasets as described in section 3.2 above. The benefits of such data are startlingly obvious and due to the matched longitudinal nature of the data, for the first time it became possible to conduct studies that could control for both observed and unobserved heterogeneity in workers *and* in the firms in which they were employed. Empirically this meant that much more of the variation exhibited in labour markets could be explained and it also allows the issue of omitted variable bias (as a result of not including both worker and firm effects) to be resolved.

The creation of this new type of dataset also brings with it new implications surrounding identification and estimation of the model. (See section 3.3.2) Identification requires repeated observations on workers, repeated observations on their employing firms and sufficient movement of workers between firms. In solving the identification problem, by ensuring ‘enough; data, this in itself then presents a problem for the estimation of the model. Initial studies relied on statistical approximations for estimation, whilst Abowd, Creecy and Kramarz (2002) first presented methods that could provide the exact solution to the estimation problem.

Estimation is possible using a fixed effects framework. In its very basic form these models can be solved by inserting dummy variables for both workers and firms, and solved using OLS. The actual estimation problem is essentially a computational one. The datasets in question are typically very large and often contain hundreds of thousands of observations. The full least squares dummy variable method is simply too computationally intensive in terms of time and memory constraints. Andrews et al (2006) propose practical solutions to this problem using spell fixed effects (section 3.4.3) and a solution identical to the full least squares dummy variable method, although computed in a slightly different way (3.4.4). Each method still has their related shortcomings i.e. spell fixed effects, although it can provide consistent estimates for coefficients on the observed explanatory variables, it cannot separately identify the unobserved individual worker and firm heterogeneity. Their least squares dummy variable method (termed

FEiLSDVj) suffers from the same problems as the full dummy variable solution in that the computational constraints will simply be too great for most researchers.

Cornelissen (2008a; 2008b) provides a memory saving way in the form of a Stata module that can estimate the full least squares dummy variable method. It provides a simple and effective way of estimating the model and obtaining estimates of all parameters of interest; including the contribution of the unobserved individual worker and firm effects.

The empirical framework presented for the analysis within a labour market context will be used to conduct an empirical analysis within the context of health care. Scottish dental data will be used as it is similar in nature to the types of datasets described above; it is essentially is a matched patient provider dataset. The fixed effects methods proposed by Andrews et al. (2006) and Cornelissen (2008a) will be adopted to analyse the variation in the use of dental radiographs across Scottish dental practitioners. Having described the factors that are likely to impact on the provision of radiographs and presented these within a simple theoretical model (3.5.2), section 3.5.3 presents the general specification that will be estimated in the empirical analysis presented in Chapter 5.

Chapter 4: Dental Care Provision in Scotland

4.1 Introduction

Knowledge of the institutional arrangements and policy context is essential to both interpreting and modelling data. This is what this chapter provides. Chapter 2 discussed the importance of analysing variation in health care delivery from a theoretical and empirical perspective. Recent developments in micro econometrics, in particular within the labour literature, have opened up the possibilities for empirical investigation. There has been significant progress in data collection processes and analysis which have enabled the development of the matched data sets described in Chapter 3. An aim of this study is to try and transfer the ideas from the labour literature to a health care setting in an attempt to provide further empirical analysis on health care variations.

The discussions in Chapter 3 highlighted the importance of not only data quality, but also its structure, in being able to carry out critical empirical analyses. In order to reproduce anything similar to the types of recent studies carried out in the labour market setting, it is necessary to have access to similar types of high quality health care data sets. This study has the major advantage of having a wealth of health care data readily available here in Scotland. The Information Services Division (ISD) is Scotland's national organisation for health information, statistics and IT services, and even state on their website that, *"...Scotland has some of the best health service data in the world. Few other countries have information which combines high quality data, consistency, national coverage and the ability to link* *data to allow patient based analysis and follow up".*[14] ISD works in partnership with many health care organisations to build national databases of health care information. One such organisation is The Health Informatics Centre (HIC) at the University of Dundee. This is a purpose built research environment where information about health from different sources is linked. Most of the data used here comes from NHS Tayside or ISD Scotland.

One aim of this particular study was to exploit some of the data resources available within Scotland. Dental data was the obvious starting point given that what is essentially a matched patient provider dataset is already available. The data set in question is taken from the Management Information and Dental Accounting System (MIDAS). This is an administrative database used mainly to process payments made to dentists and contains details of all NHS dental treatment carried out in Scotland. The MIDAS data is described in detail in the next chapter (section 5.2) but in order to fully understand and appreciate the data it is first necessary to consider the framework that exists in Scotland for the provision of dental care. The remainder of this chapter will help to provide some insight into the market for dental care and the institutional structure (section 4.2) in which this service is provided. Section 4.3 provides a brief overview of the current uptake of services in Scotland. In section 4.4 the Scottish system is compared to other dental care systems in the rest of the UK and finally section 4.5 concludes.

4.2 Institutional Structure of NHS Dental Services

Patients in Scotland can receive dental care from a variety of providers in both the public and private sector. There is evidence that private sector dentistry is

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[14] http://www.isdscotland.org/

on the increase, however it remains small in comparison to the level of dental care provided in the public sector[15]. Given that the vast majority of dental care is undertaken by the public sector, this section describes only the organisational structure for dental services provided in NHS Scotland.

4.2.1 Dental Care Providers

(NHS) dental care providers operate in 3 categories; in the primary care setting, General Dental Services (GDS) and Community Dental Services (CDS), and in the secondary care sector Hospital Dental Services (HDS).

4.2.1.1 General Dental Services

GDS is by far the biggest provider of dental care and the majority of general dental practitioners in Scotland are employed within this service. This is usually the first point of contact that patients have with dental treatment. The dentists are in effect 'high street' dentists and are independent contractors working on behalf of NHS Boards, with which their contracts are held. In most cases they provide the full range of NHS treatments, which patients can register to receive. There is no minimum NHS commitment required and in fact they do not have to provide NHS treatment at all. It is becoming increasingly common to find that most will work both for the NHS and privately. In a report produced by The NHS Information Centre (2010), it is estimated that on average dentists in Scotland spend 76.6% of their working week on NHS care and 23.4% on private care.[16]

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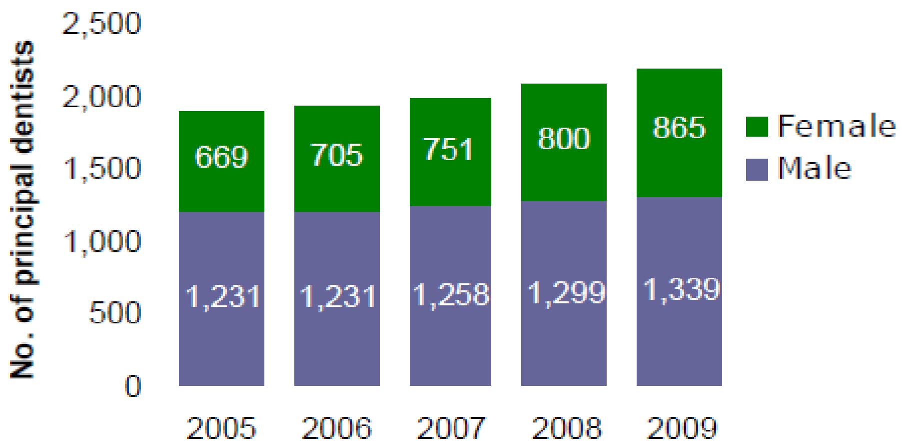
[15] More Details can be found in *An Analysis of Dental Workforce in Scotland: A Strategic Review,* 2010. This describes in detail the recent trends in the numbers registered with Denplan.

[16] The report finds regional variation for the proportion of time spent on NHS dentistry. Dentists in the West spend, on average, 86.2% of their time on NHS care, whilst those in the North spend only 54.9% of their time on NHS care.

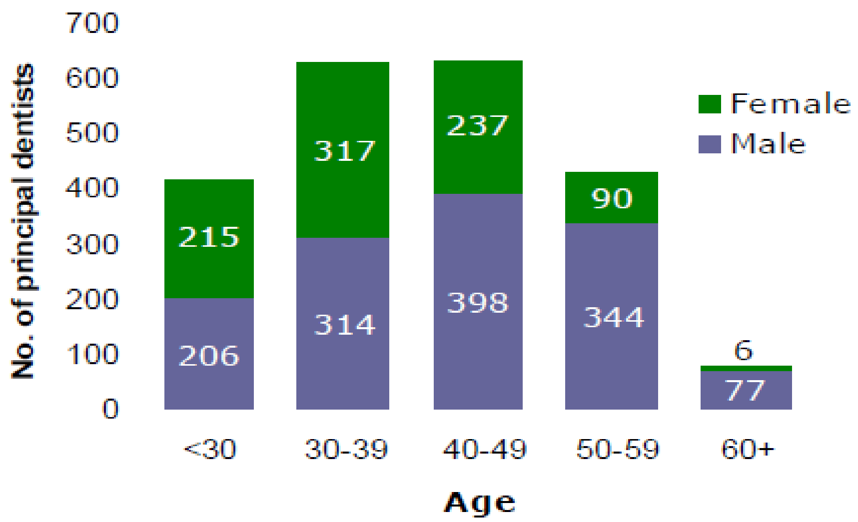
The independent contractor dentists are responsible for providing the staff, premises and equipment required to deliver services. There is no restriction on where to practise so provision is quite varied across Scotland, which is increasingly becoming the point of a lot of policy discussion in this area. In March 2009 2,204 of GDS dentists were principal independent self employed contractors. Figures 4.1 and 4.2 below show the breakdown by gender, and by age and gender.[17] Latest figures from ISD Scotland report that as of 31 March 2010, the number of principal non-salaried GDS dentists had risen to 2,313.[18]

Figure 4.1: Number of Principal Non-Salaried GDS Dentists by Gender, 31 March 2009



[17] Source: Scottish Dental Practice Board, Annual Report, (SDPB 2009)
[18] http://www.isdscotland.org/isd/5898.html

Figure 4.2: Number of Principal Non-Salaried GDS Dentists by Age and Gender, 31 March 2009



The GDS is also made up of a number of salaried dentists. Salaried dentists have the same remit as self employed dentists and provide the same range of NHS services; however they are remunerated differently to their independently contracted counterparts. The introduction and expansion of these posts in the GDS is a relatively recent phenomenon in Scotland, mainly created to provide services in areas where NHS Boards felt there was some degree of unmet need. Salaried dentists are quite often recruited to areas where access is limited, for example, due to retiring practitioners not being able to sell their practice or because dentists have moved into the private sector (Scottish Executive 2006). Currently there are 424 salaried dentists, a figure that is up 9.6% on the previous year (March 2009).[19] Figure 4.3 below shows the trend in headcount of GDS dentists over the last 10 years.

[19] Latest figures from ISD Scotland, 31 March 2010

Figure 4.3: Trend in GDS Headcount (at 31 March) in Scotland, 2000-2010[20]

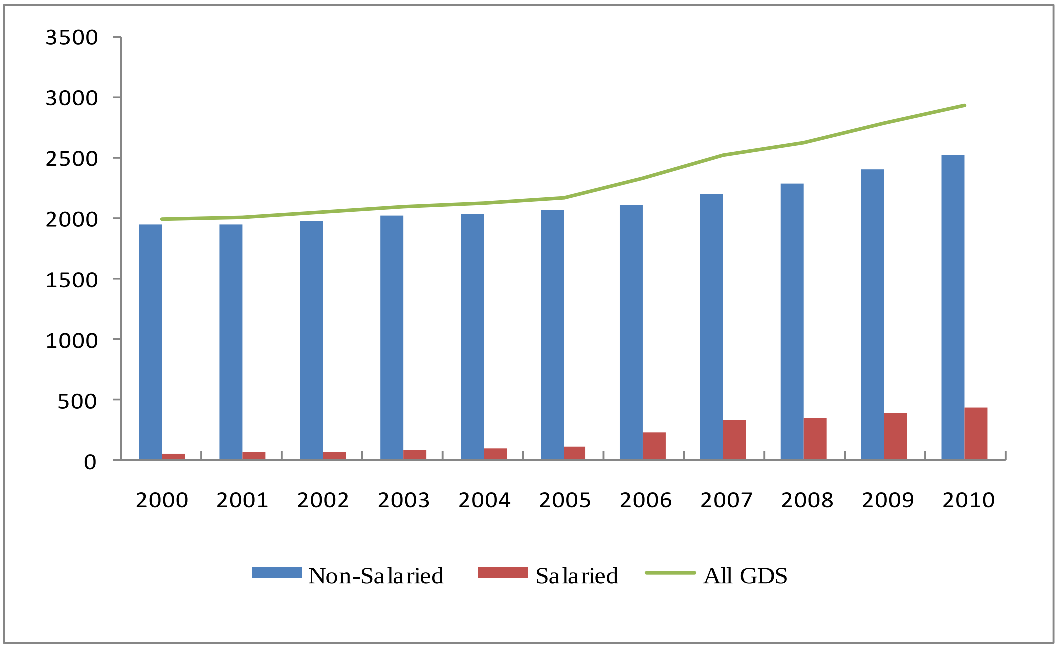


Table 4.1 presents the number of practices for salaried and non salaried dentists in Scotland.

Table 4.1: The Number of NHS GDS Practices by NHS Board; 31 March 2009[21]

NHS Board	Non-salaried Practices	Salaried Practices	Combined non-salaried/salaried Practices	Total
Scotland	**903**	**57**	**16**	**976**
Ayrshire & Arran	63	1	-	64
Borders	16	6	-	22
Dumfries & Galloway	26	4	-	30
Fife	54	3	-	57
Forth Valley	45	4	2	51
Grampian	71	1	-	72
Greater Glasgow & Clyde	259	6	2	267
Highland	47	16	4	67
Lanarkshire	89	1	-	90
Lothian	151	3	-	154
Orkney	1	1	-	2
Shetland	2	5	2	9
Tayside	76	-	-	76
Western Isles	3	6	6	15

[20] Source: ISD data. Please note that due to recent changes and improvements in measuring salaried dentists, significant increases are seen in the data from 2005 onwards.
[21] Source: Scottish Dental Practice Board, 2009

4.2.1.2 Community Dental Services

The CDS is made up of approximately 400 staff that are directly employed and managed by NHS Boards. Their remit is essentially two fold; the first is in providing a complementary service to the GDS by identifying and treating special needs groups or those resident in long-stay care. In recent years there has become an increased commitment to act as a ‘safety net’ for those patients who do not obtain treatment from GDS. CDS are also known to play a significant role in service delivery in remote and rural areas across Scotland. Their services are provided at over 300 locations, in fixed or mobile clinics. The second aspect of the remit is the role in dental health promotion and preventative public health programmes for children. The service undertakes annual inspections of children’s oral health via the National Dental Inspection Programme in primary schools. In addition to dentists, CDS employs a wider team of dental nurses, hygienists, therapists and admin staff. Within this service sector, children are not charged for treatment and adults who would normally be eligible to pay under GDS pay charges on a very limited basis, for example, when bridges/dentures etc. are required. Data on the treatment carried out in the CDS is collected via the Scottish Morbidity Record (SMR13), in a similar way to the data collected in a hospital setting.

A Review of NHS Primary Care Salaried Dental Services was published by the Scottish Executive in 2006. This review recommended that the current salaried GDS and CDS should combine to form a new Scottish Public Dental Service, with a remit that would combine that of both sectors, i.e. provision of care for people with special needs, complement the current GDS particularly in remote and rural areas and continue to be involved in a public health and promotion role. Reporting arrangements for this group of dentists have often varied between boards in the way dentists are classified, but, in light of this review, from April 2008 the primary care salaried dental practitioner classification has gradually been phased in to cover the activities of both groups. Since April 2008, the previous data collection scheme for NHS community dental services ceased and a new system was set up to collect data uniformly across the two groups. The process of forming a completely merged sector is still ongoing.

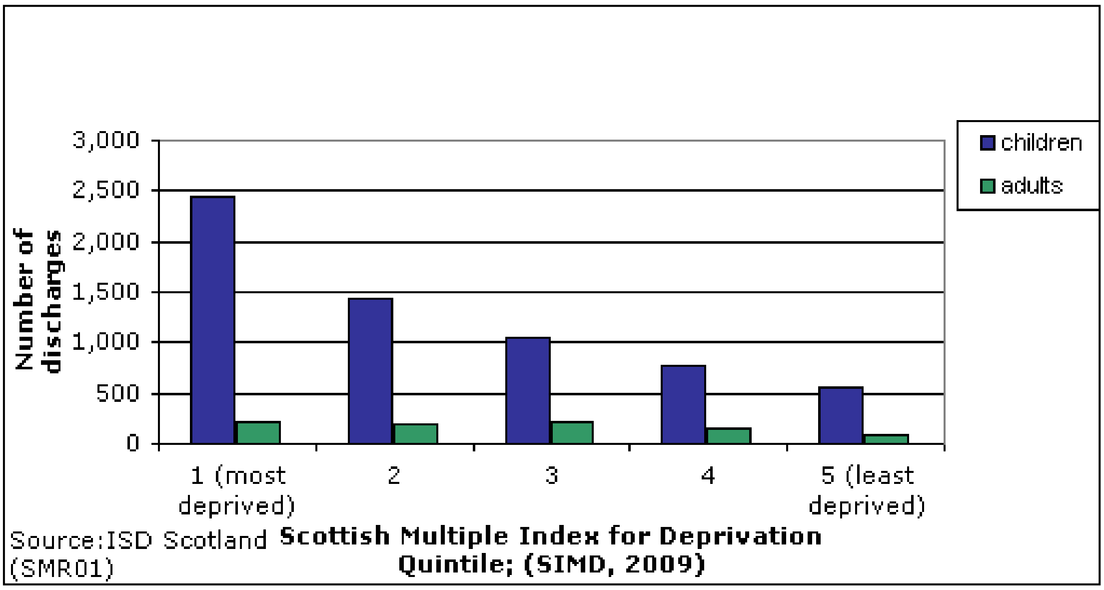
4.2.1.3 Hospital Dental Services

Finally, HDS are consultant-led services that treat patients on referral from, mostly medical and dental practitioners, but also from consultants in other disciplines, and from emergency dental services. As of September 2009, HDS contained 376 dentists, a figure that is up 31% on the previous year.[22] Through the hospital dental service, patients are admitted either as inpatients or day cases to hospitals, but can also be treated at outpatient clinics. Data relating to dental care in HDS is collected in two ways. One is via the Scottish Morbidity Record (SMR01) which contains information on inpatients and day cases, and the other is via an aggregate that provides information on all attendances at hospital (ISD(S)1). One in 18 new attendances to outpatient clinics is to a dental specialty and 1 in 72 hospital discharges are from a dental specialty.[23] The service is not only provided in the dental hospitals in Dundee and Glasgow and the dental institute in Edinburgh, but also in many general hospitals across Scotland. Hospital Dental Services are usually provided when more specialist treatment is required, for example, orthodontics, surgical and paediatric dentistry. The most common reason for planned hospital

[22] ISD Scotland - http://www.isdscotland.org/isd/5345.html
[23] Data taken from ISD Scotland - http://www.isdscotland.org/isd/4669.html

admission to a dental specialty is for the extraction of multiple teeth, particularly for children and among those from the most deprived areas of Scotland. This procedure accounts for 42% of all admissions where a procedure took place, with 61% of these were on patients residing in SIMD 1 and 2 (most deprived). Figure 4.4 below highlights this aspect further by showing the total number of inpatient and day case discharges from having had this procedure carried out.

Figure 4.4: Total Discharges (inpatients and day cases) for Procedure 'Extraction of Multiple Teeth' by Age Group; 31 March 2009



4.2.2 Dentist Remuneration

As outlined above, General Dental Services comprises the largest sector where NHS dental care in Scotland is undertaken. In the majority of cases, and certainly during the time period that the empirical analysis will cover, a patient will be treated in a practice by either a self-employed GDS dentist or a salaried GDS dentist. The system of recording and collecting data on the treatment carried out by, either a non-salaried or salaried GDS dentist is the same. This process is different to that found in the community and hospital services. It is for these reasons that the focus group of this study is GDS dentists. As mentioned above, the remit of salaried and self employed dentists is exactly the same and, the NHS procedures offered by both types of dentist will be the same. The difference between the two practitioners comes in the form of their remuneration contract.

4.2.2.1 Statement of Dental Remuneration (SDR)

Regulation 22 of the Scottish Legislation: The National Health Service (General Dental Services) Regulations 2010 requires that Ministers clearly provide and set out information on remuneration for dentists in Scotland. They are required to do this in the form of 'Determinations' which are detailed and published in a statement known as the Statement of Dental Remuneration (SDR). Amendments to this statement are permitted, though only after consultation with the relevant people and/or groups from within the profession, and any agreed change must be published.

The latest amendment to the SDR is amendment 116, which was announced in March 2010 and has been in effect since April 2010.[24] In this latest version, there are a total of 15 Determinations, providing detailed guidance on all aspects of remuneration for both self-employed and salaried dentists in Scotland. The main purpose of amendment 116 is to inform NHS Boards, Practitioner Services and dental practitioners themselves of the introduction of non-time limited registration for both children and patients. This means that from 1 April 2010 all existing and new patients registered with a dentist under a continuing care and capitation arrangement will be registered for life. Registration arrangements will no longer

[24] There have now been five further ammendments to the SDR, with the latest being announced on 7th September 2011. The main purpose of these further ammendments were to announce a change in the scale of fees, to provide information on the change in the Scottish Index of Multiple Deprivation (SIMD) Classification, changes to recruitment and retention allowances, and the introduction of Childsmile Practice and the new Index of Orthodontic Treatment Need into the SDR.

lapse after a set period. Prior to April of this year, the time period was 36 months, and until April 2006 the time was 15 months. A registration arrangement will, however, come to an end, and continuing care or capitation payments cease, where Practitioner Services have determined that a patient has died, moved out of the country or registered with another dentist in Scotland.[25] A further memorandum produced by The Scottish Government Primary and Community Care Directorate (2010), states that amendment 116 to the SDR inserts new provisos in Determination I, to the items relating to capitation and continuing care payments. It advises that where a patient has not attended the dentist for 3 years or more, then the payments will be reduced to 20% of the relevant fee. The other change to the SDR as announced by the memorandum is a change to Determination XII, i.e. a change to the remote areas allowance.[26]

4.2.2.2 Salaried Remuneration

The remuneration of salaried dentists is relatively straight-forward, guidelines for which are detailed in Determination II of the SDR. These dentists are employed by NHS Boards throughout Scotland and simply receive a fixed salary. They may also be part of the salary plus bonus scheme. Salaried dentists on this scheme receive an annual rate plus a bonus which is related to gross fee income. From April 2009, this was 37.1% of gross fee income in excess of £59,304. The SDR outlines the pay scales and terms for all full and part time salaried dentists. On top of the fixed income, salaried dentists can also receive a range of allowances. What these allowances are and the conditions of their entitlement are also listed in the SDR.

[25] See Memorandum PCA(D)(2010)1, http://www.sehd.scot.nhs.uk/pca/PCA2010%28D%2901.pdf
[26] For more details on amendment 116 to the SDR, refer to http://www.sehd.scot.nhs.uk/pca/PCA2010(D)03.pdf

They range from recruitment payments to payments for out of hours emergency provision. Payments are also made to dentists working in remote and deprived areas. Alongside the SDR, summary leaflets on grants and allowances for salaried GDS dentists are also provided by The Primary Care Division of The Scottish Government. These were first introduced in 2003 and help to raise awareness of the various grants and allowances salaried dentists can claim.[27]

4.2.2.3 Self-employed Remuneration

The remuneration of self-employed GDS dentists is more complex. These dentists are remunerated under a hybrid system where a capitation and continuing care arrangement is supported by an item of fee structure. This type of system for remunerating non salaried GDS dentists has broadly been in operation for many years in one form or other. The decision for remuneration to be based on a scale of fees for each individual treatment carried out dates back to the beginning of the UK National Health Service in 1948. The fee scale was developed to reflect the time taken to carry out a given treatment. The belief was that more complex procedures will take longer and therefore warrant a higher payment. Like today, the original GDS dentists had a right to accept or refuse any patient, establish a practice in any location and could also continue to treat privately if they wished. In the years following the creation of a GDS in Scotland, there were many problems with the remuneration system. Firstly the levels of demand for dental care were hugely underestimated, this coupled with the fact that the fee scale meant dental earnings, and in turn government expenditure far outweighed what was predicted. A number of measures were taken to try and control this. Dental earnings were capped; the fee

[27]The latest leaflet for salaried dentists can be found in Annex B of Government memorandum PCA(D)(2009)6 http://www.sehd.scot.nhs.uk/pca/PCA2009(D)06.pdf

scale was reduced, and in 1951 patient cost sharing was introduced, through the patient charge. For more information on the patient charge refer to section 4.2.3.

Despite the ongoing criticisms of the system, there were no real changes to remuneration until the new Dental Contract was introduced in October 1990. With the new contract came the introduction of the continuing care and capitation fees. GDS dentists now entered into an ongoing contractual arrangement with patients and received additional payments on a monthly basis, dependent on the number of adults (continuing care) and children (capitation) they had registered. Essentially this structure still forms the basis of the system that exists in Scotland today. As in the case of salaried dentists, the SDR provides all information relevant to remuneration for self-employed dentists. Determination I lists the scale of fees for a given year. This section is sub divided into a further 15 sections referring to all the different areas/types of dental treatment that is provided, for example Diagnosis, Preventative Care and Surgical Treatment. Guidance relating to the conditions of payment of remuneration and information relating to any additional payments is also documented. In relative terms the fees have remained unchanged and still aim to reflect the time taken to carry out a given treatment/procedure. They are reviewed annually by the Doctors' & Dentists' Review Board (DDRB), who often agree to a uniform % increase across the scale. In September 2009, the fee scale was increases by 0.21% on the previous year.

The item of service fee structure has led to a very complicated dental care system where there are over 400 individual treatments, each with their own individual fee attached. The complexity of the system, particularly for patients, has often been a major criticism and there is now a Scottish Government commitment to review and simplify the system. Discussions around implementing a new SDR, however, are still ongoing. The remaining determinations in the SDR document the allowances applicable to self-employed dental practitioners. There are many 'top-up' payments made similar to those for salaried dentists, like the remote areas allowance and recruitment and retention allowances. There are the additional continuing care and capitation payments, but also seniority payments and practice allowances.[28]

4.2.3 Patient Charges

When introduced in Scotland, NHS dental care, like most other health care services, was free at the point of use. However, it quickly became apparent that this could not be sustained and so a system of patient cost sharing was put in place to help cover the fee component of self-employed remuneration. The patient charge was not applicable for everyone and a set of exemption and remission categories exist for those in society who might find it difficult to pay. These are usually on the grounds of age and/or income. Full details of these can be found in Table 4.2 below.

[28] Full details can be found in the SDR or the grants and allowances leaflet, see http://www.psd.scot.nhs.uk/professionals/dental/docs/Dental_Allowance_Guide_2009-2010_v2.pdf

Table 4.2: NHS Exemption & Remission Categories for Dental Treatment

Exemptions[1]
Under 18
18 and in full time education
Pregnant
Nursing mother (had a baby in the last 12 months)
Remissions[2]
Patient or partner receives income support
Named on a valid NHS tax credit exemption certificate
Receiving pension credit guarantee credit
Receiving income based job seekers allowance
Named on a HC2 certificate (entitled to full help with costs)
Named on a HC3 certificate (entitled to partial help with costs)

[1] No charge, fees paid by NHS boards on behalf of patient
[2] Charges exist but patient is entitled to help with paying it

Currently non-exempt patients pay 80% of the cost of treatment up to a maximum limit of £384. Charges are paid directly to dentists by patients. In 2009/10, this amounted to £52.2 million[29]. NHS Boards fund the difference between the patient charge and self-employed item of service remuneration, and cover the costs of any exemptions and/or remissions. Latest figures from SDPB (2010) show that £32.3 million was paid by local Boards in remissions, and £29.9 million in exemptions.

4.2.4 Cost of Provision

The cost to the Scottish Government and NHS Boards of providing GDS dental services is made up of a number of elements. Child fees are paid to dentists by local NHS Boards and consist of item of service and capitation fees. In the case of children, the fees paid for item of service treatments are much less that capitation fees. During 2009/10, item of services represented approximately 44% of fees; whilst capitation fees were 56%. The current cost to the GDS of treating a child in

[29] Scottish Dental Practice Board Annual Report, 2009/10

Scotland is £58, down from £59 in the previous year. The total cost of child dental care for the year ending March 2010 was £60.0m. Adult fees consist of item of service and continuing care fees, where the majority is item of service (87% in 2009/10). The current cost of treating an adult in the GDS has increased from £37 in 2008/09 to £41 in 2009/10, with the total cost of adult dental care for the year ending March 2010 being £154m. (SDPB 2010)

Table 4.3 below summarises the last three years of authorised fees of dental practitioners working in NHS general dental services. It contains information on the patient charge and the amount paid by NHS Boards to cover exemptions and remissions. Gross fees include any adjustments and referrals. The table can be used to assess changes in clinical activity for salaried dentists across Scotland, compared to non-salaried dentists. The numbers in the table for salaried are purely notional, based on the information collected on GP17 forms; salaried dentists do not actually claim item of service or registration fees, but since details of the treatment carried out is collected in the same way, suitable comparisons can be made.

Table 4.3: Fees Authorised (£000s); Year ending 31 March[30]

	Non-Salaried Dentists			Salaried Dentists[1]		
	2007	**2008**	**2009**	**2007**	**2008**	**2009**
Gross Fees	188,320	198,724	219,804	5,308	7,025	9,385
Net Fees paid by NHS Boards (including exemptions and remissions	142,272	152,214	169,932	3,826	5,209	7,212
Capitation	29,499	31,953	36,043	845	1,324	2,016
Continuing Care	20,513	23,274	28,330	645	766	1,162
Item of Service	137,054	140,831	150,991	3,883	4,895	6,146
Patient Charge	46,048	46,509	49,872	1,483	1,735	2,173
Remissions	25,614	25,790	27,942	749	949	1,133
Exemptions	27,488	28,274	29,878	590	781	1,071

[1]Notional Fees associated with salaried dentist activity; salaried dentists do not claim item of service or registration fees

[30] Source: SDPB Annual Report, (SDPB 2009)

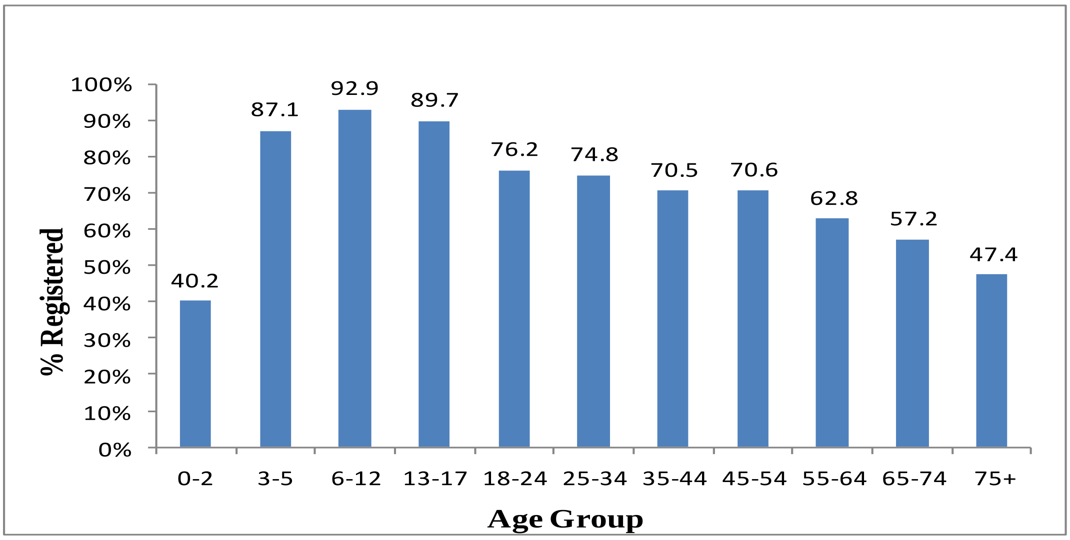
It is clear from Table 4.3 that the proportion of general dental services activity by salaried dentists is very small relative to non-salaried dentists, and in 2009 activity would have amounted to only 4% of total fees. It is however a growing sector and in the space of two years, activity has increased significantly, shown by an 88% increase in the level of net fees, from £3.8m in 2007 to over £7.2m in 2009.

The level of fees paid to non-salaried dentists has increased by approximately 20% in the 2 years from March 2007 to March 2009. Much of the increase can be explained by increases in the capitation and continuing care payments which have increased by 22 and 38%, respectively, as a result of increasing numbers of both adults and patients registered with a GDS dentist. The proportion of gross fees attributed to remissions and exemptions has declined slightly over the period. In 2007, exemptions and remissions accounted for 28% of all fees, but this had fallen to 26% by 2009. A similar trend is observed with the salaried fees.

4.3 Utilisation of NHS Dental Services in Scotland

This section presents a brief overview of the current uptake of NHS dental care in Scotland. It uses information on registration rates to show the percentage of the population that are registered with an NHS dentist, hence providing some indication of those accessing dental services. The latest information on registration rates, published by ISD in July 2010, provides data as at 31 March 2010 and, in line with a new rolling timetable for publications, also as at 30 June 2010. Figure 4.5 shows the percentage of the population, by age group, currently registered with an NHS dentist.

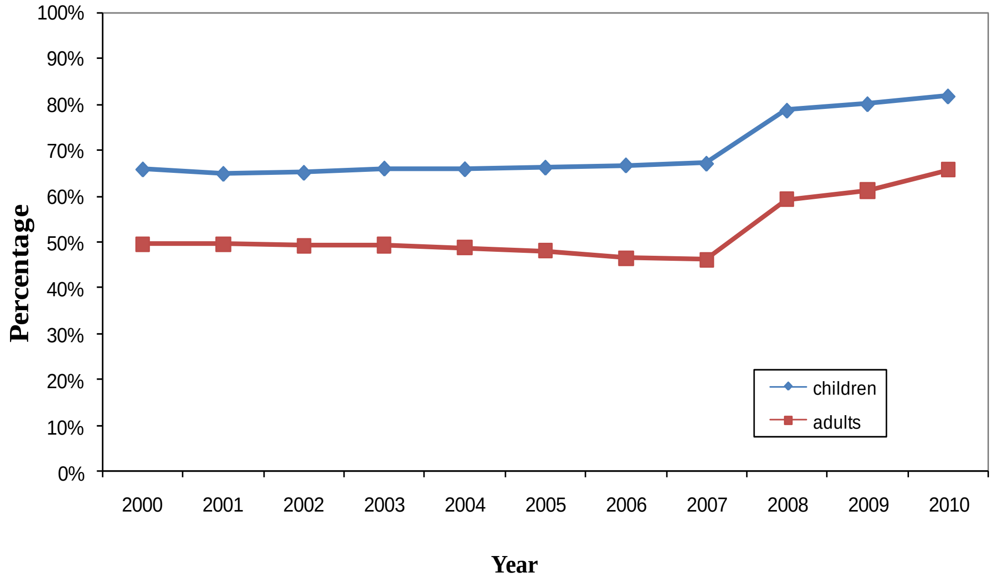
Figure 4.5: Percentage of Population Registered; 30 June 2010



The latest figures show that 82.4% of children and 67% of adults are registered with a dentist. Figure 4.6 shows the trend in adult and child registration rates over the period from March 2000 to March 2010. Between 2000 and 2007, registration rates for children remained fairly constant, however rates for adults steadily declined from 49.6% in 2000 to 46.2 % in 2007. In 2008, however, there was a large increase in registration rates for both adults and children. This increase has continued for both populations, but more so in the case of adult registrations.

The significant increase in 2008 and the continued trend may in part be explained by changes made to registration policy. Prior to April 2006 registrations would lapse after 15 months if patients did not visit their dentist. From April 2006, this time limited increased to 36 months, which means patients would remain registered for longer, unless de-registered. This is likely to be a contributing factor in the recent rise in registration rates and the trend may be set to continue as the current registration period is now non-time limited – a policy which came in to effect on 1 April 2010.

Figure 4.6: NHS Registration Rates at 31 March 2000-2010



Changes are currently underway in the way registration data will be analysed in Scotland. Up until March 2010, analysis has been based on the postcode of the practice where the patient was registered. However, this has now changed and registration data will be based on the postcode of the registered patient. This will provide more accurate and meaningful data. There have also been quality improvements in the data collection process facilitated by the inclusion of the Community Health Index (CHI) number to the patient registration dataset. This has enabled duplicate registration records and records of deceased patients to be removed from the data.

ISD also plan to introduce a ‘participation’ measure to supplement registration data. The aim of this is to provide more information on actual activity patterns of dentists and utilisation of services by patients. It will show information on the number of times a patient visits their dentist and has treatment over a one or two year period. Registration data alone cannot provide such information. Tilley & Chalkley (2005) suggested that analysing participation patterns in GDS dentistry could provide a better way of gaining information on overall utilisation and access to dental services, than simply looking at registration data on its own. They analysed individual level data on dental courses of treatment for over 35,000 patients in a six year period. The results showed that almost 80% of the adult population in Scotland did access dental care in that period, which was in contrast to the rates provided by registration data – which at the time suggested approximately 50% of the population had access to a GDS dentist. Chalkley & Tilley (2008) extended this analysis and looked at similar data over a longer time frame, 1998-2006, and found a similar result i.e. 79% of the adult population in Scotland accessed dental services in that 9 year period. The results from both analyses indicate that large numbers of adults do access dental care in Scotland, however do so quite infrequently. Looking at registration rates alone and participation rates over short intervals will not give a true indication of utilisation and access to dental care.

4.4 Dental Care Provision in the Rest of the UK

Prior to April 2006, dental care provision was similar throughout the whole of the UK, and described in detail above. The majority of dentists were independent contractors working on behalf of the NHS, via a national contract. Scotland also had an increasing number of salaried dentists and England and Wales had what are known as Personal Dental Services (PDS). PDS were introduced to tackle some of the major problems facing NHS dentistry at the time, namely access issues and poor levels of oral health. The National Health Service (Primary Care) Act 1997 provided the new arrangements in relation to the provision of dental services. This legislation saw the creation of the PDS and enabled local commissioning of general dental services by Primary Care Trusts (PCTs) in England and Wales. As a result, in 1998 a number of voluntary PDS pilot schemes were established to test alternative methods for both the provision of services, but also remuneration methods. Two main remuneration models were adopted; a salaried model and a capitation payment system. In 2003, The School of Dentistry and Health Services Management at The University of Birmingham carried out a national evaluation of the PDS pilots. In a paper that summarised the findings, Goodwin et al. (2003), found that the pilots appeared to encourage a new skill-mix, provide job satisfaction and improve working conditions. They appeared to provide the opportunity to change the culture of primary care dental provision from one based on activity and cost to one based on quality of care. The success of the pilots provided the foundation for the national introduction of local commissioning and the New Dental Contract was introduced in England and Wales on April 1 2006.

In December 2008, Alan Johnson, the Health Secretary at the time, commissioned an independent review of NHS dentistry. Professor Jimmy Steele was selected to chair the review and published the findings in June 2009 (Professor Jimmy Steele for Department of Health 2009). The report summarised the reforms of 2006 and highlighted the three key issues as follows:

- Responsibility for planning and servicing NHS dental services was devolved to local PCTs
- The system of patient charges was changed, resulting in a reduction in the possible number of charges from around 400 to just 3
- The mechanism by which dentists are paid to deliver services changed from one based on item-of service fees to one where providers are paid an annual

sum in return for delivering an agreed number of courses of treatment, which were weighted by complexity.

Dental procedures in England and Wales are now categorised according to the level of complexity and are converted into what are known as units of dental activity (UDA). These units of activity are provided under the contract in ‘banded courses of treatment’. A national reference period was set which ran from 1st October 2004 until 30th September 2005. The activity undertaken by dentists in terms of UDAs and childhood capitation was then converted to an overall financial contract value and dentists were then offered the contract for a minimum three year period, with this guaranteed three years protection of earnings. In return dental practitioners contract to provide an agreed annual level of NHS commitment – which is based on the number and complexity of the courses of treatment provided in the reference period.

Patients in England and Wales now face a much simplified charging system. There are 3 bands of co-payment and payment is fixed regardless of the number of treatments carried out. Table 4.4 below provides a summary of the classification system for the new dental contract. It shows the different treatment bands, along with the types if treatment items covered in each band. It also shows the corresponding UDA for each band and the current patient charge for patients in England and Wales (Department of Health 2010).

Table 4.4: Treatment Bands, Treatment Items, UDAs and Patient Charges

Treatment Band	Treatment Items	UDA	Patient Charge	
			England	Wales
1	examination, diagnosis, preventative advice, scale & polish if needed	1	£16.50	£12.00
2	Band 1 plus fillings, root canal and extractions	3	£45.60	£39.00
3	Bands 1 & 2 plus any laboratory work such as crowns dentures and bridges	12	£198.00	£177.00

There has been widespread criticism of the new contract and initial reaction by the dental profession was somewhat negative, with a number of dental practitioners opting not to sign the new contract (Carvel 2006). A number of assessments and reviews have been undertaken in recent years that suggest there are still many problems within NHS dentistry and the new contract has not achieved what it set out to do.

In July 2008, The House of Commons Health Select Committee published a report on dental services (Health Select Committee 2008). They agreed to assess the impact of the new contract against four main criteria issued by the Department of Health, on which they claimed its policies should be judged (Department of Health 2007). These criteria were patient experience, clinical quality, PCT commissions and dentists' working lives. The report concluded that the new contract was *"......in fact so far failing to improve dental services measured by any of the criteria."* (p.49) The Independent Review of NHS Dentistry (Professor Jimmy Steele for Department of Health 2009) followed shortly after and made a number of recommendations on how the service could be improved, and specifically recommended introducing an annual per person registration payment to dentists within the contract. The NHS White Paper, Equity and Excellence: Liberating the NHS (Department of Health 2010a) set out the government's long term vision for the future of the NHS. With respect to dental services, it sets out ways to improve quality of care and improve access to services. There is an additional focus on improving the oral health of school children. In light of Steele's independent review of dentistry, this report proposes the introduction of a new dentistry contract following a period of consultation and piloting. As a result, on 16 September 2010, the government announced that a national steering group would be set up with the aim of publishing proposals for piloting a new dentistry contract by the end of 2010. In a statement to the press Lord Howe said *".....As set out in the White Paper – we intend to bring a new dental contract based on registration, capitation and quality."*(Department of Health 2010b)[31]

It is clear from above that the process of finding the best system for the provision of dental services in the UK is an ongoing and complex one. Currently all four nations are reviewing the way dental services are provided, although the timetable for any changes to the contract in Scotland or Northern Ireland is not certain. Northern Ireland is closer to implementing a change than Scotland and negotiations on a new contract between the Department of Health, Social Services and Public Safety (DHSSPS) and the Dental Practice Committee of the British Dental Association (BDA), have been underway since November 2006. Professor Ciaran O'Neill, a health economist, from Queens University Belfast was tasked to conduct a review of existing dental remuneration systems from across the world, and then recommend a suitable model for Northern Ireland. A framework for the new contract is now in place and is based on a blended system of remuneration comprising payment through a block component alongside a limited item of service component (DHSSPS 2009). The DHSSPS and BDA are currently working towards setting up pilot sites to test the new contract, with a view to rolling it out across Northern Ireland in the near future.

[31] The government in England are currently piloting three different contract models in 62 sites across the country, to inform the development of a new national dental contract. More details can be found at http://www.pcc.nhs.uk/dentalpilots

4.5 Conclusion

This study makes use of Scottish Dental Care data and will investigate the determinants of and variation in the use of dental radiographs across dental practitioners in Scotland. This chapter describes the institutional framework within which dental services are provided in Scotland, in order to inform the development and interpretation of the following empirical analysis.

Scotland has a poor record when it comes to oral health and it is widely acknowledged that compared to other European countries, oral health standards are much lower in Scotland. This has led to huge investment being poured into dental services by the Scottish Government, in an effort to combat this problem. A number of oral health and dental service targets have been set by the Government and a range of initiatives have been introduced, with the specific aim of improving the oral health of the Scottish population. For children such initiatives include the Childsmile programme and initiatives such as the introduction of free dental check-ups for all since April 2006 and non-time limited registrations since April 2010 should further help to improve access to dental care and in turn lead to better oral health. Registration rates have been increasing in recent years and currently 82.4% of children and 67% of adults are registered with an NHS dentist.

Dental care is provided in both the public and private sectors, although the private sector remains very small in comparison. Data from Denplan suggests that there is an increasing trend in the use of private dental care in Scotland and data from the BHPS also shows an increase in the number of reported private check-ups. Since 2006 this trend has started to decline, though has been matched with an increase in the percentage of the population reporting an NHS check-up[32]. This observation is possibly linked to a policy change at that time, which saw the introduction of free dental check-ups for all in Scotland.

Analysis in this study is restricted to general dental services (GDS), whereby dentists work in one of two settings; either as an independent self-employed contractor (‘high street’ dentist) or as one directly employed by NHS Boards and paid a fixed salary. The remit of both non-salaried and salaried dentists and the system of recording and collecting data on the treatment carried out by either type of dentist is the same; the only difference between the two practitioners comes in the form of their remuneration contract. These factors are central to the empirical analysis presented in Chapter 5 as there is evidence that the remuneration structure and patient cost sharing have an impact on the amount of treatment provided by dentists (Chalkley & Tilley 2006; Chalkley et al. 2010).

Section 4.4 discussed the institutional framework in which dental services are provided in the rest of the UK. The recent changes to the payment structure in England and Wales means that replicating a similar study for these countries may be difficult. Although N. Ireland has a system that closely mirrors the Scottish system, the need for change is also on the agenda, again making it difficult to assume similar results may be achieved in other areas. The differences that exist between Scotland and the other UK nations, however may present an opportunity to conduct a natural experiment, perhaps similar to that conducted by Chalkley et al. (2010).

[32] More Details can be found in *An Analysis of Dental Workforce in Scotland: A Strategic Review*, 2010

Chapter 5: Data and Empirical Analysis

5.1 Introduction

Chapter 4 described the institutional framework in which dentistry is carried out within Scotland, with particular emphasis on dentistry within the NHS setting. It also provided policy background and an insight into contractual arrangements and how interventions have been targeted. The aim of this study is to use matched data to identify and measure sources of variation in dental health care across Scotland. There have been previous studies that focus on dental health care as a whole, for example, Chalkley & Tilley (2006) and Young (2009) consider overall dental treatment intensity, however this study aims to consider a specific aspect or intervention by dental practitioners. From the data available the chosen application to consider for further analysis was dental radiographs, which this chapter addresses.

The review of the literature on variation presented in Chapter 2 identified a number of potential sources or determinants of variation that can arise in any health care setting. Many of the studies described focussed solely on how economic incentives may impact on treatment outcomes. This is an area that this thesis will also address; given that the Scottish dental care system means that potentially economic incentives, financial or otherwise, may play a part in explaining the variation in dental treatment. However, the discussion in Chapter 3 illustrates that potentially a much greater range of factors than economic incentives are likely to have an impact on the treatment decision of whether to provide a dental radiograph or not. Patient, dentist and practice characteristics all potentially influence this decision.

The empirical analysis that follows uses the theoretical framework set out in Chapter 3 (section 3.5.2) and draws on principal agent theory and agency models.[33]

Using this simple framework it is possible to identify a number of hypotheses to test in the empirical analysis:

H1: Dentists on a Fee-for-Service contract are more likely to provide a radiograph, relative to those on a fixed salary (provided the fee exceeds the marginal cost)

H2: Patients who are exempt from the patient charge (fully insured from the cost) are more likely to demand a radiograph or acquiesce to receiving a radiograph, relative to those who pay for treatment

Interactions between the contract of the dentist and the exemption status of the patient will also be taken into account. This suggests a further two hypotheses can be tested:

H3: Dentists on a Fee-for-Service contract will provide more radiographs when the patient is exempt, relative to a fixed salary dentist

H4: Dentist specific effects contribute more to the observed total variation in the provision of radiographs relative to patient specific effects.

These hypotheses have not been identified from the theoretical model *per se*; rather they have been identified using the model and by considering in detail the factors that are likely to impact on the decision to provide a radiograph. This, along with the estimation strategy proposed for dealing with matched data; inform the empirical analysis of what could be considered a complex economic process. On the demand side we consider the moral hazard issue in health care markets and consider

[33] For a detailed discussion on principal-agent theory refer to Laffont & Martimort (2002)

the fact that health insurance has the effect of reducing the price of treatment that the patient faces, hence leading to excess demand (Pauly 1986; Zweifel & Manning 2000). We therefore might expect that demand for dental radiographs to be increasing in the degree of insurance (patient co-payment). On the supply side we consider the dental physician agency effects identified in Chalkley & Tilley (2006). If the world is really one of physician agency, only dentist characteristics and remuneration contract would matter. However, if the world is one of bargaining between dentist and patient, both patient and dentist characteristics, patient insurance and dentist remuneration will affect observed treatment. These theories help motivate the empirical equation that follows and allows the testing of hypotheses 1-4 above.

Of equal importance to what can be observed and measured, are the unobservable characteristics of both the dentist and patient, which will also be addressed in the empirical analysis. These factors have been identified in the theoretical literature mainly in the context of possible mitigating factors for the potential opportunistic behaviour of physicians. For example, Gravelle (1999) recognised that the fact patients can choose their GP; means there is an incentive to increase both the quality of care and the effort put into providing care. Physicians have to compete for patients and so some of their market power is reduced. Another suggestion is that physicians' to a certain extent will show some degree of benevolence towards their patients. There is also a growing literature on the impact of the patient-doctor relationship (Vick & Scott 1998) and patient preferences in analysing the behaviour of physicians.

Chapter 5 is essentially the empirical component of the thesis and is organised as follows. Section 5.2 describes in detail the data to be used in the analysis. The data collection and processing is discussed as well as detailed descriptive statistics for the sample. Section 5.3 contains the empirical analysis. Sections 5.3.1 and 5.3.2 use the framework developed in Chapter 3 to present the models to be estimated and section 5.3.4 reports the results. Finally section 5.4 discusses the results and concludes.

5.2 Data

5.2.1 Data Collection

The process of recording and collecting data on dental care and treatment within the Scottish General Dental Services (GDS) begins primarily at the dental practice level. Any patient receiving NHS treatment will have it detailed in what is known as a treatment plan. This plan provides an outline and complete breakdown of all the work/treatments required to address the particular problem and restore satisfactory levels of dental health. The plan may be as simple as a routine examination or scale and polish, however in many cases it will be more complex and will contain a range of different treatments, for example examination, radiograph, filling and scale and polish. The details of the plan and the treatment required collectively represent a full course of treatment, which may be completed at one visit but can also be over the course of a number of visits.

All details of the treatment provided are recorded in the dental practice on GP17 forms. These forms consist of a number of different parts, where Part 3 is where all information relating to the treatment is recorded. Parts 1 and 2 contain information relating to the patient and dentist respectively. Part 4 provides information on the patients' acceptance of the treatment and details of how payment will be made. Parts 5 and 6 can be used by the dentist to provide any further information relating to the treatment, and finally parts 7 and 8 are declarations made by both the patient and dentist on completion of treatment. A similar form, GP17(O), exists when the treatment in question is orthodontic.[34] It contains similar information to the GP17, with the only difference being the inclusion of more detailed information on specific treatments relating to orthodontics. The information on these forms therefore provides a major source of dental treatment data collected in NHS Scotland.

As discussed in chapter 4, section 4.3.2, the remuneration for self-employed dentists working in the GDS sector is a hybrid system where a capitation and continuing care arrangement is supported by an item-of-service fee structure. This fee component is financed in part by patients through the 80% patient charge, whilst NHS Boards fund the difference and cover the cost of any exemptions and remissions. The GP17 and GP17(O) forms by way of design therefore help facilitate the fee-for-service component of dentist remuneration. Importantly, it should be noted that although Scotland's second type of GDS dentist i.e. those on fixed salaries, are remunerated differently, all the information relating to their work is recorded and collected in exactly the same way as for the fee-for-service self-employed dentists. This allows for a direct comparison between the two types of dental remuneration contracts to be made.

[34] Copies of the GP17 and GP17(O) forms have been provided by NHS Tayside and have been included in the Appendices (Appendix 1)

5.2.2 Data Processing

The processing of the data collected on the GP17 and GP17(O) is the responsibility of the Practitioner Services Division(PSD)[35] in Edinburgh. The forms themselves can be submitted, or the information can now be submitted electronically through the Electronic Data Interchange (EDI). This system was introduced in November 2000, and now over 400 practices use EDI to submit treatment details to be processed for payment. This represents approximately 2.5 million item-of-service claims per year for 1.5 million patients registered for NHS general dental services.[36] All of the information collected in Edinburgh is entered into a large database known as The Management Information and Dental Accounting System (MIDAS). This is an administrative database operated solely by PSD and used primarily to process the payments made to dentists. It contains details of all NHS courses of treatment carried out and paid for in Scotland – approximately 4 million courses per year.

Within MIDAS each course of treatment (represented by each individual form) is referred to as a ‘claim’, given the use of the database for dentists to claim payment. Each new claim entered into the system is given a unique number or identifier, which is simply incremental to the previous claim. The database also contains information on each NHS dentist, again with each dentist having their own unique number. This includes the dentists’ list number(s) and details about their practice. Finally all the information relating to patients is recorded. In the same way each dentist and each claim have unique identifiers each patient registered to receive

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[35] Practitioner Services is one of the 11 divisions within NHS National Services Scotland (NNS). They provide patient focused services such as the transfer of medical records between GP practices, assisting patients to access GP and dental practices, as well as assisting practitioners to maintain accurate and up-to-date patient registers. Practitioner Services (Dental) pay dentists, on behalf of the NHS Boards, for the NHS work they carry out. They also monitor and verify payments made to dental practices.

[36] For more information see http://www.psd.scot.nhs.uk/professionals/dental/edi.html

NHS dental care is also given a unique identifier. For any new claim submitted to PSD, within MIDAS it is possible to use the information on the forms to run what is known as a matching algorithm. This will enable the linkage of a given claim to any existing claims for that individual. If, however, no existing claims are found, then a new unique patient identifier is created. Again this number is simply incremental to the last patient number created.

The nature of the data held within MIDAS allows for all the information relating to patients, dentists and claims to be linked. In this case this linkage is established through the dentist list number, which is recorded on each treatment form. The result is that MIDAS provides a rich dataset with the opportunity to follow both patients and dentists over time. In other words it is analogous to a matched patient provider dataset similar to the matched employer-employee dataset described in Chapter 3.

5.2.3 Data Extraction

For the purpose of this analysis, a random sample was extracted from the MIDAS database. Given its use in the process of paying dentists the data contained in MIDAS is not available to the public, however for research purposes, at the time of this study an anonymised version was held at the University of Dundee within the Dental Health Services Research Unit. By all accounts it was a complete replica of that held in Edinburgh, however with all personal information that could identify any given dentist or patient removed.

The extraction of the sample is facilitated by being able to ‘query’ MIDAS to do different things. For example MIDAS can be queried to obtain details of all courses of treatment over a given time period. Constraints can also be placed on queries and essentially you can ‘ask’ MIDAS for the exact data you require, with very little manipulation required afterwards to construct a complete dataset. In this case the random sample was generated by first identifying patients with the unique identifier ending in 000 – 029 during the relevant time period i.e. from 1st April 2000 to 31st March 2005. MIDAS could then be queried to extract all claims relating to these patients made by both self-employed and salaried dentists. Patients with identifiers ending in 025 and 026 were excluded from the sample due to an idiosyncratic problem where the query kept failing whist trying to extract the data. All claims associated with ‘non-standard’ list numbers were also removed from the extraction. Dentists in Scotland can provide care under different list types, for example assistant lists, trainer lists, emergency and temporary lists. This means that sometimes claims made under these types of list numbers may contain treatments performed by another dentist. It was therefore decided to exclude them from the analysis.

Tables 5.1 and 5.2 below provide an illustrative guide as to what the data extracted from MIDAS looks like and highlights the *linkage* that exists in the data. The first table combines the patient information with the course of treatment information. For simplicity the detail relates to one patient only, with unique identifier (pid) 1.

Table 5.1: MIDAS: Patient and Course of Treatment Extract

lnum	pid	clid	trid	fee (£)	item_code	sd_sdr	pcy	er	age	sex
1	1	1	1	5.95	1(A)	SDR74	Jul-99	FULL	38	1
1	1	1	2	37.5	14(C)(1)(1)	SDR74	Jul-99	FULL	38	1
2	1	2	3	7.5	1(A)	SDR101	Nov-06	FULL	45	1
2	1	2	4	15.6	14(A)(3)	SDR101	Nov-06	FULL	45	1
2	1	2	5	45.3	14(C)(1)(1)	SDR101	Nov-06	FULL	45	1
3	1	3	6	16.25	27(E) Upper	SDR101	Dec-06	FULL	45	1
3	1	3	7	101.6	27(B)(2) Upper	SDR101	Dec-06	FULL	45	1
3	1	4	8	15.35	28(A)(1) Upper	SDR101A	Jan-07	FULL	45	1

1(A) is exam, 14(C) is filling (composite resin), 14(A) is filling (amalgam), 27(E) is impression tray, 27(B) is denture, 28(A) is repair or alteration to denture

The example above shows that for this given male patient (in the data sex=1 is male), the courses of treatment recorded cover a period between July 1999 and January 2007. The column headed *er* refers to the exemption or remission from the patient charges that may be applicable. In this case the patient pays the full charge i.e. they are non-exempt. The table also provides details about the actual items of treatment that were given and the corresponding fee paid to the dentist. In all, 9 treatments were provided over a series of 4 different courses of treatment (shown from unique claim identifier, *clid*). The patient was treated under 3 different list numbers, which may or may not indicate three different dentists as dentists may have more than 1 list. The real benefit to the researcher of MIDAS is how this information can then be linked back to individual dentists, thus allowing complete information for each and every course of treatment carried out in Scotland. The key to this is provided through the dentist list number, ***lnum***. Table 5.2 below illustrates the type of information that can be extracted from MIDAS relating to dentists.

Table 5.2: MIDAS: Dentist Extract

did	**lnum**	sal	NHS Board	depcat	sex	dage
1	1	0	1	1	F	62
2	2	0	2	6	M	58
2	3	0	1	2	M	58
3	4	0	1	2	M	56
3	5	0	2	6	M	56
4	6	0	1	5	M	51
4	7	0	1	6	M	51
4	8	1	3	3	M	51

The unique dentist identifier, *did*, shows that this table provides information on 4 different dentists, all, apart from dentist 4, working solely on a self-employed contract (*sal=0*). Dentist 4 provides treatment under 3 different list numbers, one of which is under a salaried contract. Information is also provided on the age and gender of the dentists and details relating to the practice they work in i.e. the health board it is situated in and the corresponding deprivation category. As already mentioned, it is the list number that enables the linkage of this information back to each individual patient and course of treatment. By combining this table with the previous through ***lnum***, it is possible to establish that the patient in fact only saw two different dentists over the period as the work carried out on lists 2 and 3 was by the same dentist, i.e. *did* equal to 2.

The above tables show a simple example of how the data extracted from MIDAS can provide a rich dataset for further analysis. To complete the process, the data was merged in Stata where all the linked information remained. The individual treatment items in any course of treatment were combined in such a way that each line in the dataset now represented an individual claim, complete with its own unique identifier. The items were also converted to dummies representing broad treatment categories, for example examination and radiograph items were classified as diagnosis, fillings and crowns were termed conservative etc.[37] The result gave a unique 'matched' patient provider dataset that could readily be used to analyse not only the variation in the provision of dental radiographs, but many other questions/hypotheses about dental care provision in the Scottish NHS.

The nature of the data processing stage in MIDAS, with its allocation of incremental unique identifiers to both dentists and patients, ensures as representative a sample as possible. Not only is the data found to be representative of the population, but it can confidently be used as a reliable data source given its role in the paying of dentists. Practitioner Services (Dental) also undertake extensive pre-payment validation on dental payment claims, and there is an element of ex-post validation carried out through the Scottish Dental Reference Service (SDRS) who monitor the quality and probity of dental treatment in Scotland by examining a sample of patients each year.

5.2.4 Data Description

The random sample extracted from MIDAS contained a total of 453,751 claims made by 2,419 distinct dentists for 103,757 distinct patients. Close inspection of the data revealed minor coding errors that required correction and new variables were created for the age of the dentist (at the time of treatment as opposed to the time of data extraction) and to include an interaction term between the dentist contract type and patient exemption status. The sample was further reduced to remove any claims for patients under the age of 18 (63,470 claims) and over the age of 75 (15,693 claims). The under 18s were removed as the data collected for them is not directly comparable with the rest of the sample due to the fact the dentists are not

[37] The broad treatment categories relating to each treatment item are in line with that set out in the Statement of Dental Remuneration (SDR).

remunerated in the same way for this age group. Although in many cases data for certain treatments are recorded, it may not reflect the true number of treatments carried out. With regard to the over 75 age group, the data revealed a number of observations for patients over the age of 90 and in some cases over the age of 100. It was not possible to check if indeed these reflect the true ages of individuals or was perhaps the result of human error in the data collection and recording process. It was therefore decided that there should be a cut off point to ensure the reliability of the data. This cut off age of 75 was chosen in line with Chalkley & Tilley (2006), in which a similar dataset was used. This left a sample for analysis consisting of 364,729 claims made by 2,377 distinct dentists for a total of 80,234 different patients. In the sections that follow, the regression variables are described and discussed.

5.2.4.1 Dependent Variable

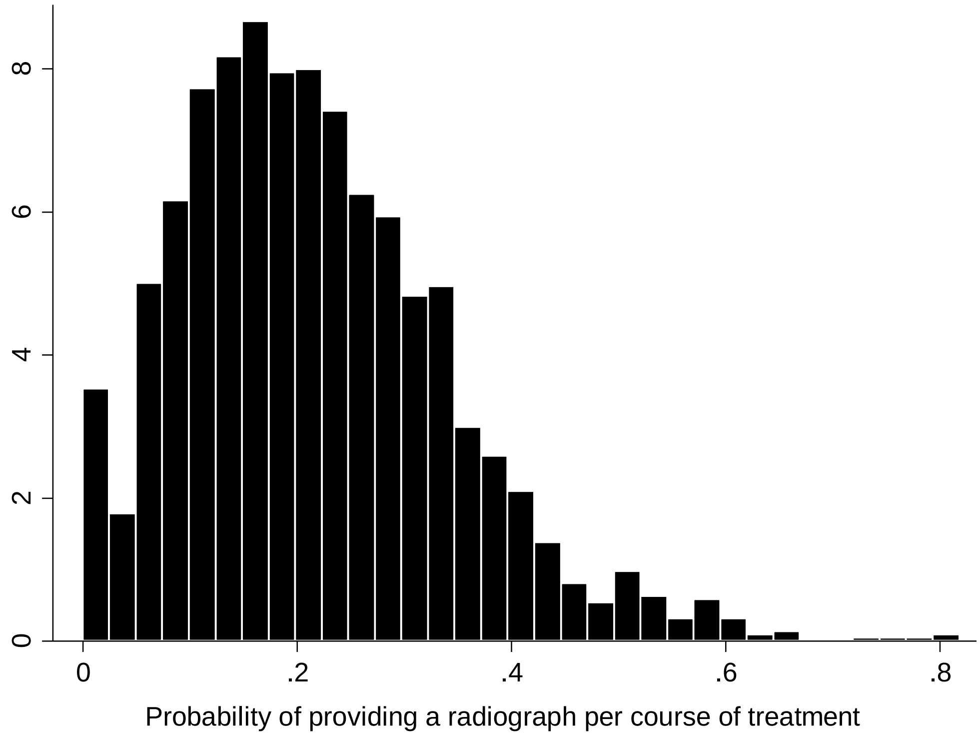
In the regression analysis presented in section 5.3, the aim is to analyse and account for the variation in the use of dental radiographs across GDS dentists in Scotland. The variable of interest in the data is *code2a1* and refers to a given type of dental radiograph. This is a binary variable that indicates whether or not a given course of treatment contained at least one of these radiographs. This name is in line with the code used in the SDR, where radiograph 2a1 refers to a small film radiograph. Other radiograph codes in the data refer to medium and large films, along with more complex radiographs that tend to be used in orthodontic treatment.

The small film radiograph (code2a1) is by far the most common radiograph given and is therefore the focus of the analysis.[38]

Of the 364,729 claims in the sample, 69,987 (19.2%) contained at least one of these radiographs. Figure 5.1 below shows the distribution in the provision of radiographs across dentists in Scotland and shows the likelihood that each dentist will provide a radiograph in any given course of treatment[39]. It is clear that there is quite a wide spread in this probability. The majority of dentists will radiograph anywhere between 10 and 40% of the time, whilst almost 4% of dentists almost never provide them. However there are small proportions that tend to use radiographs much more often, with some dentists having almost all their courses of treatment containing one of these small films. There are 5 dentists in the sample that provide a radiograph in more than 70% of their courses of treatment. It is also worth noting that the number of observations that each of these dentists had ranged from 144 to over 400, so there is some confidence that these dentists really are much more likely to provide radiographs when compared to most other dentists in the sample.

[38] Figures from the Scottish Dental Practice Board Annual Reviews show that each year approximately 95% of all radiographs carried out in Scotland are small film radiographs.
[39] Please note that any dentists with less than 6 observations have been removed from the sample so as not to skew the distribution

Figure 5.1: Variation in the Provision of Radiographs across GDS Dentists in Scotland, April 2000 - March 2005



Given that dentists within the General Dental Services (GDS) in Scotland can provide treatment under two types of contract, it is of interest to examine if there are any obvious differences in the relevant radiograph distributions. Figures 5.2 and 5.3 illustrate these for self-employed and salaried dentists respectively[40]. The distribution for self-employed dentists is very similar to that of the overall distribution. There are still dentists (61, with observations ranging from 6 to over 200) that appear to never provide a radiograph and in contrast also a small proportion that have a tendency to provide radiographs about 80% of the time.

[40] As in Figure 5.1, all dentists with less than 6 observations have been removed from the sample.

Figure 5.2: Variation in the Provision of Radiographs across GDS Self-Employed Dentists in Scotland, April 2000 - March 2005

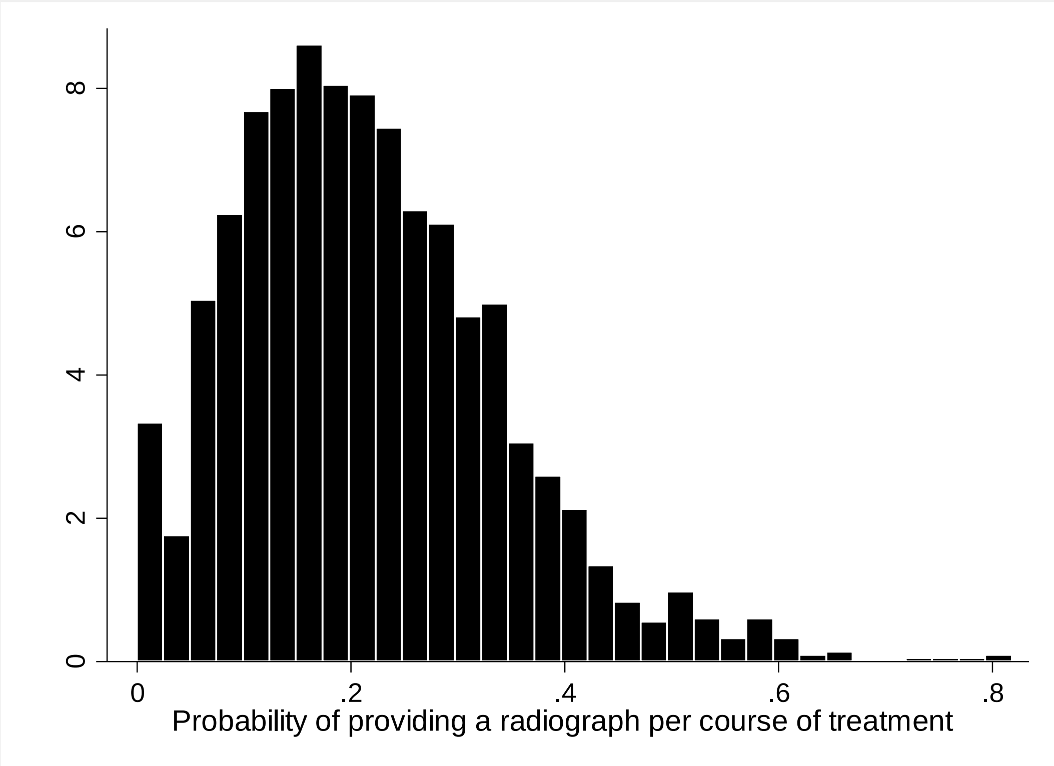
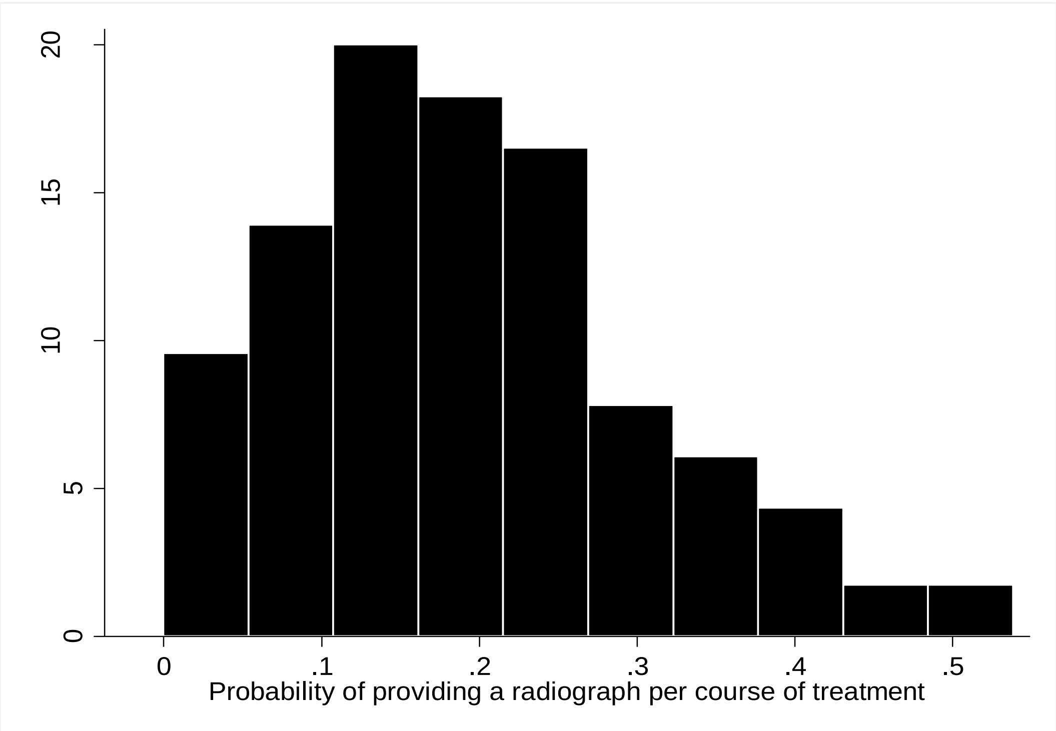


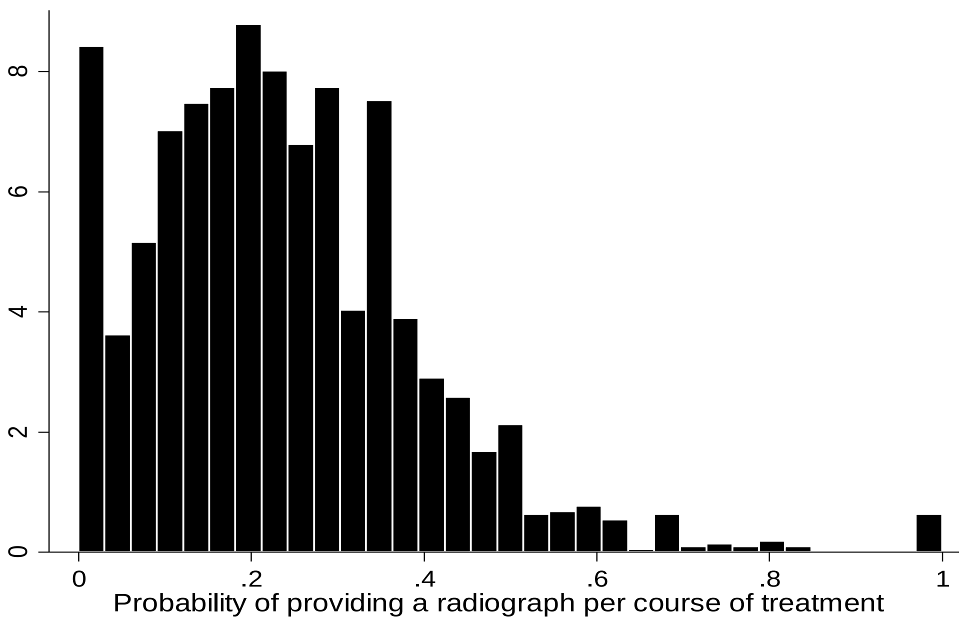
Figure 5.3: Variation in the Provision of Radiographs across GDS Salaried Dentists in Scotland, April 2000 - March 2005



Although Figure 5.3 shows there is still variation in the provision of radiographs across salaried dentists, the distribution is quite different from that for all dentists and the self-employed dentists on their own. It is clear that there are no salaried dentists with a high propensity to provide a radiograph, with the highest probability being a little over 50% of the time.

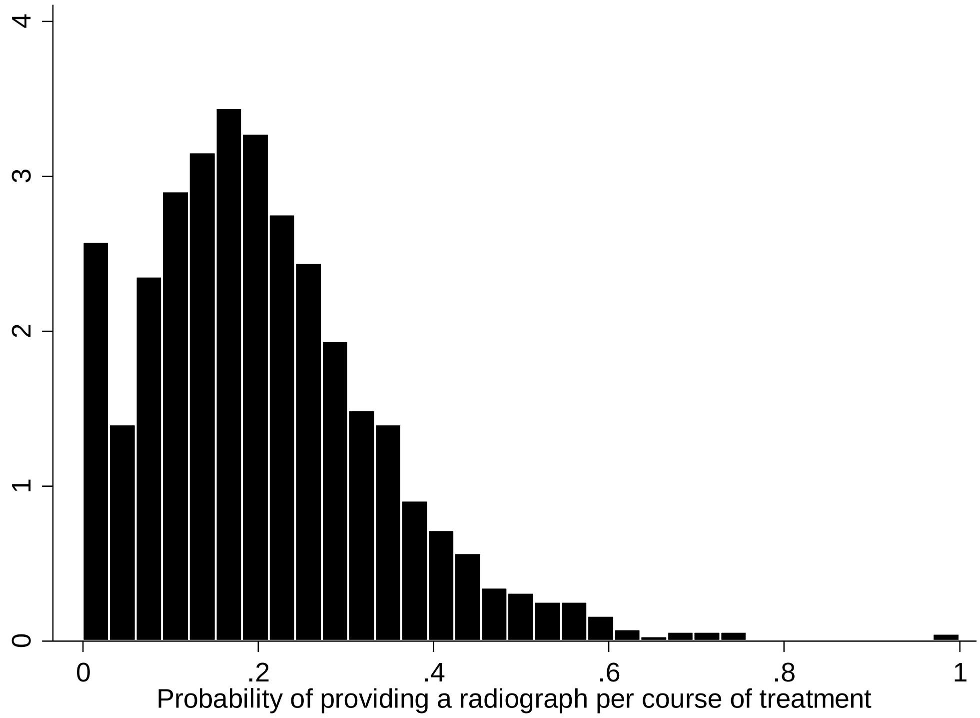
Not only is the contract of the dentist a point of interest in this study as a potential source of variation in the provision of radiographs, but so too is a key characteristic of the patients, namely whether or not they contribute to the cost of their treatment. This is captured in the data using the *exempt* variable. It therefore is also useful to consider the distribution in the provision of radiographs across the two patient types, i.e. exempt and non-exempt. Figures 5.4 and 5.5 illustrate this, respectively[41].

Figure 5.4: Variation in the Provision of Radiographs to Exempt Patients across GDS Dentists in Scotland, April 2000 - March 2005



[41] As before, dentists with less than 6 observations have been excluded from the sample

Figure 5.5: Variation in the Provision of Radiographs to Non-Exempt Patients across GDS Dentists in Scotland, April 2000 - March 2005



Similarly, the above figures show little deviation from the overall distribution of radiographs across all patients. If anything, the ‘spread’ in the distribution may be even greater when broken down by patient type. In particular, there are a number of dentists (14, with the number of observations ranging from 6-62) that provide a radiograph in every claim when the patient is exempt from paying the patient charge.

The data presented in Figures 5.1 to 5.5 reveal that firstly there appears to be a large variability in the distribution of radiographs across dentists in Scotland, regardless of the contract type of the dentist or if a patient pays for treatment or not. Secondly the general pattern of the distribution is similar across the different specifications with the most obvious difference being for the salaried dentists, where in general they have a lower likelihood of providing radiographs. There is potentially a subtle difference between exempt and non-exempt patients, where there are a greater proportion of dentists that tend to always provide a radiograph when the patient does not pay for treatment. Certainly based on this information alone, it is difficult to conclude one way or another, the impact of contract or demand side cost sharing on the variation in the provision of radiographs.

5.2.4.2 Treatment Variables

A number of treatment variables *prev, perio, cons…..trauma* etc. are included in the analysis in an attempt to identify and take account of overall dental condition. Each refers to a broad treatment category as defined in the SDR and is represented by a dummy variable. They are equal to 1 if the course of treatment included any form of the given treatment and 0 otherwise. For example, in the case of *prev*, this would equal 1 if the course of treatment included advice on oral hygiene techniques or surface applications, such as fissure sealants. In the case of *surg*, this would be equal to 1 if the course of treatment contained any form of surgical procedure, e.g. extractions or any post operative care required.

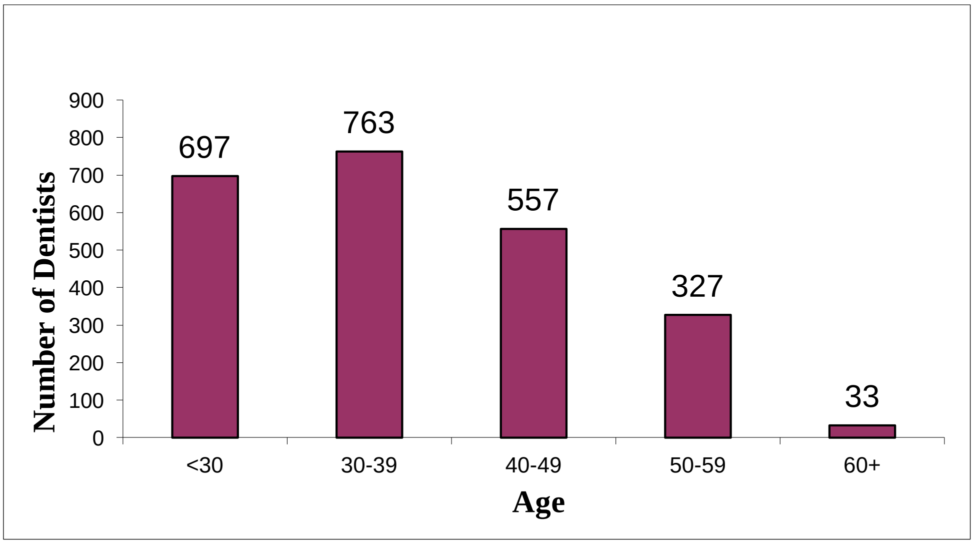
19.2% of all claims in the sample contained at least one small film radiograph (*code2a1*). In broad treatment terms they come under the dummy variable for diagnostic treatment. In studying the possible sources of variation in the use of radiographs it is useful to consider how overall dental condition or need might impact on this. To do this it is useful to consider what other treatments are commonly found alongside radiographs. Does it follow that given one type of treatment, a radiograph may be required or given their diagnostic nature, is it more common to find radiographs being used for diagnoses in certain types of treatment, for example, a logical case might be when surgical treatment is required.

The data does in fact reveal that the most common treatments found alongside radiographs are conservative, periodontal and surgical. 64% of all claims containing a radiograph will also have some form of conservative treatment, for example a filling. 59% of claims with radiographs contain periodontal treatment and 17% contain surgical treatment. 40% of claims with radiographs will have both periodontal and conservative treatment, and 6.7% will contain all three alongside the radiographs. This certainly suggests that there may be some link between certain treatment groups and the likelihood of being given a radiograph. Is it the case that treatments from these groups represent poorer oral health and if so, is radiograph provision therefore a function of dental need? These factors have to be taken into account and controlled for in the regression analysis.

5.2.4.3 Dentist Characteristics

A number of variables are included in the regression to account for dentist specific characteristics. These consist of the standard age and gender variables, but also the contract type of the dentist i.e. whether the dentist is self-employed or salaried. Figure 5.6 illustrates the age distribution of the 2377 dentists in the sample.

Figure 5.6: Age Distribution of Dentists at Time of First Claim



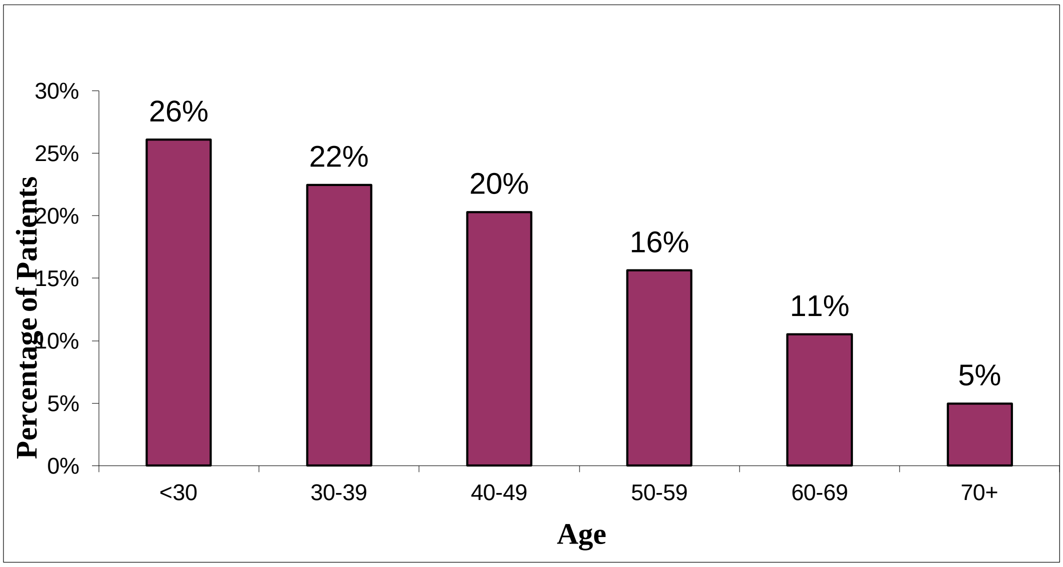
The majority of dentists in the sample are between the ages of 30 and 39 (32%), although a similar percentage (approx 30%) of the sample are below the age of 30, with the youngest dentist being 22. 1% of the sample is over the age of 60, with the oldest dentist being 66.

The sample of dentists is made up of 1508 males (63%), accounting for 73% of all claims and 869 females (37%), and accounting for 27% of all claims. When the gender split is considered by contract type of the dentist, the result is quite similar. In total 2238 dentists are always self-employed, with 1428 being male (64%). 100 dentists in the sample work only on a salaried contract, with 60% of this group being male. There is a slight change to the pattern when the group of dentists that work as both self-employed and salaried is considered. In total there are 39 dentists in the sample that do this, with approximately an even split between males and females. (20 of the 39 dentists are male.)

5.2.4.4 Patient Characteristics

As in the case for dentists, the regression models also include a number of variables to control for individual patient characteristics. Again age and gender is included, but a further important variable is added, one that can take into account whether the patient pays for their dental treatment or not. The dummy variable *exempt* is used to indicate if a patient has to contribute to the cost of treatment or not, and is a good way to help control for different 'types' of patients in the sample. Figure 5.7 shows the age distribution of the 80,234 patients in the sample.

Figure 5.7: Age Distribution of Patients at Time of First Course of Treatment



The greatest proportion of the sample can be found in the youngest age category, with a steady fall in the proportion in each category as age increases. Since the sample was restricted to patients between the ages of 18 and 75, 26% of the patient population are between the ages of 18 and 30, and only 5% are between the ages of 70 and 75.

The gender breakdown of patients shows that 46% (36,916 patients) are male and 54% (43,318) are female. Data on the exemption status of patients show that 63% (50,502 patients) of the sample are non-exempt and therefore always pay for dental treatment, 24% (19,613 patients) don't ever pay for treatment, and the remaining 13% (10,119 patients) have both paid for treatment and been exempt throughout the sample period. The majority of claims in the sample (65%) are made for treatments given to non-exempt patients, with similar proportions attributed to patients who are solely exempt or have switched between exempt and non-exempt, 18 and 17% respectively.

In terms of the gender breakdown, in the case of non-exempt patients, there is almost a 50:50 split, with 50.5% of non-exempt patients being male and 49.5% being female. However, when it comes to patients who are always exempt, and have changed between paying and not paying for treatment, in both categories the percentage of the sample that are female is higher, 60% of exempt patients are female and 65% of those that have been both are female, thus suggesting that females are more likely to be exempt from charges that males.

5.2.4.5 Further Controls

A number of other variables are entered into the regression models to try and further control for different types of patients and dentists, and also any regional or time effects. The dummy variable *depcat* represents the deprivation category associated with the dental practice location. This is because, at least during the sample period, dentist's capitation and continuing care payments were weighted according to the deprivation category of the practice. Deprivation is measured on a scale that runs from 1 to 7, where 1 represents the least deprived and 7 represents the most deprived. This variable is used as an additional proxy for patient 'type'. Although it is linked to the postcode of the dental practice, and a better measure would take into account the patient postcode, this information was not available in the data at the time the analysis was conducted. The data shows that the majority of claims made are on behalf of patients attending dental practices within depcat 4, whilst the fewest claims were made on behalf of patients from practices in the most and least deprived areas, 6% in each.

The variable *lastvisit* is another variable that may define a particular type of patient and be linked to the probability of receiving an radiograph. It is a measure in months of how long it has been between treatments. The data shows that the average time for patients between visits was 7.6 months. It is important to note that the inclusion of this variable removes all patients' first visits from the sample and therefore excludes those with only one visit. This reduces the number of observations (claims) in the regression models from 364 729 to 286 843.

Twelve dummy variables termed *sdr* are included to control for any changes that might occur over time as the statement of dental remuneration (SDR) fee scale is revised. There is no set time at which these changes occur but in this sample they are at approximately 6 monthly intervals. The omitted category, sdr1 represents the fee scale in operation at the beginning of the sample period and all effects are relative to this, thus effectively controlling for changes to the nominal fees.

Finally dummy variables are included to indicate the health board of the practice. This is to try and account for any regional differences that might exist.

5.2.4.6 Descriptive Statistics

Descriptive statistics of the dataset described above are presented in the following tables. Table 5.3 gives a breakdown by contract of the dentist and Table 5.4 a breakdown by exempt and non-exempt patients. From Table 5.3, the data suggests that self-employed dentists are more likely to provide radiographs than salaried dentists, with 19.2% of claims made by self-employed dentists containing at least one radiograph, compared to 17.9% of claims for salaried dentists.

Table 5.3: Descriptive Statistics by Dental Contract

Variable	Description	Self-employed			Salaried		
		Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
x-ray (code2a1)	Equals 1 if radiographic examination carried out	358406	0.192	0.394	6323	0.179	0.383
prev	dummy variable = 1 if this course involved preventive care	358406	0.001	0.023	6323	0.002	0.042
perio	dummy variable = 1 if this course involved peridontal treatment	358406	0.546	0.498	6323	0.367	0.482
cons	dummy variable = 1 if this course involved conservative treatment	358406	0.419	0.493	6323	0.362	0.481
surg	dummy variable = 1 if this course involved surgical treatment	358406	0.087	0.281	6323	0.109	0.312
prosth	dummy variable = 1 if this course involved prostheses, obturators and other (non-orthodontic) appliances	358406	0.079	0.269	6323	0.081	0.273
ortho	dummy variable = 1 if this course involved orthodontic treatment (major corrective work)	358406	0.001	0.031	6323	0.000	0.000
incomplete	dummy variable = 1 if this course of treatment was not completed prior to the claim being made	358406	0.007	0.081	6323	0.002	0.044
trauma	dummy variable = 1 if the claim is characterised by trauma	358406	0.001	0.024	6323	0.001	0.025
depcat	Deprivation category of the practice	358406	3.849	1.539	6323	3.645	0.941
dage	Dentist age	358406	40.189	9.724	6323	43.737	8.414
dsex	Dentist sex (male=1)	358406	0.733	0.442	6323	0.705	0.456
clpery	Claims per dentist per year	358406	68.793	32.129	6323	34.385	19.212
page	Patient age	358406	44.305	14.473	6323	44.595	14.542
psex	Patient sex (male=1)	358406	0.431	0.495	6323	0.451	0.498
exempt	Equals 1 if patient is exempt	358406	0.262	0.440	6323	0.237	0.425
lastvisit	Time since last visit (months)	282555	7.548	6.237	4288	10.017	8.334

It appears that in general this pattern is true for most other treatment types, with self-employed dentists having higher proportions of claims with the given treatment compared to salaried dentists. In most cases, however, the difference is very small. The most common types of treatment found in claims for both dental contracts are for periodontal, for example scale and polish, and conservative treatment, for example fillings and crowns. This is also where the biggest difference between the two types of dentist can be found. 54.6% of claims made by self-employed dentists contained some form of periodontal treatment, compared to 36.7% of claims made by salaried dentists. Similarly 41.9% of claims for self-employed dentists contained conservative treatment, compared to 36.2% of claims made by their salaried counterparts. Very few claims contain orthodontic treatment (possibly due to the specialist nature of orthodontics), preventive, incomplete or treatment as a result of trauma, with all found in less than 1% of claims by either self-employed or salaried dentists.

The data also suggests that there is a difference in the 'type' of patients treated by self-employed and salaried dentists. It appears that self-employed dentists treat more exempt patients. The figures here show that 26.2% of the claims for self-employed dentists were for exempt patients, compared to 23.7% of claims made by salaried dentists. Self-employed dentists also seem to treat patients that attend the dentist more regularly, given that on average the length of time since last visit was 7.5 months, compared to over 10 months for claims made by salaried dentists.

The descriptive statistics presented in Table 5.4 are separated by exempt and non-exempt patients. Based on this information alone, it appears that exempt patients receive more radiographs than non-exempt patients, with 22.5% of claims for exempt patients containing at least one radiograph, compared to only 18% of claims for fee paying patients. Again the most common treatments found in claims, regardless of the patient are periodontal and conservative. For all types of treatment, there were more claims for exempt patients than non-exempt patients. For example, 44.6% had conservative compared to 40.8%, and 12.8% contain prosthetic compared to 6.1%.

The majority of claims (98%) for both patient groups were made by self-employed dentists, thus reflecting the ratio of self-employed to salaried dentists in the sample. On average, there is no difference between exempt and non-exempt patients in terms of the time between visits, with the time being approximately 7.5 months.

Table 5.4: Descriptive Statistics by Exemption Status

Variable	Description	Exempt			Non Exempt		
		Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
x-ray (code2a1)	Equals 1 if radiographic examination carried out	95542	0.225	0.418	269187	0.180	0.384
prev	dummy variable = 1 if this course involved preventive care	95542	0.001	0.035	269187	0.000	0.017
perio	dummy variable = 1 if this course involved peridontal treatment	95542	0.577	0.494	269187	0.531	0.499
cons	dummy variable = 1 if this course involved conservative treatment	95542	0.446	0.497	269187	0.408	0.491
surg	dummy variable = 1 if this course involved surgical treatment	95542	0.130	0.336	269187	0.072	0.258
prosth	dummy variable = 1 if this course involved prostheses, obturators and other (non-orthodontic) appliances	95542	0.128	0.334	269187	0.061	0.240
ortho	dummy variable = 1 if this course involved orthodontic treatment (major corrective work)	95542	0.000	0.019	269187	0.001	0.034
incomplete	dummy variable = 1 if this course of treatment was not completed prior to the claim being made	95542	0.014	0.118	269187	0.004	0.062
trauma	dummy variable = 1 if the claim is characterised by trauma	95542	0.001	0.029	269187	0.000	0.022
depcat	Deprivation category of the practice	95542	4.345	1.576	269187	3.668	1.475
dage	Dentist age	95542	39.272	9.598	269187	40.597	9.732
dsex	Dentist sex (male=1)	95542	0.714	0.452	269187	0.739	0.439
se	Contract type of Dentist (= 1 if self-employed,0 if salaried	95542	0.984	0.124	269187	0.982	0.133
clpery	Claims per dentist per year	95542	61.494	30.992	269187	70.576	32.371
page	Patient age	95542	39.806	14.242	269187	45.908	14.217
psex	Patient sex (male=1)	95542	0.347	0.476	269187	0.462	0.499
lastvisit	Time since last visit (months)	71971	7.632	7.144	214872	7.569	5.963

Tables 5.3 and 5.4 above present descriptives for the data broken down by the contract type of the dentist and the exemption status of the patient. Although important, these are only two of the factors that are considered in this analysis. Before moving on to the main empirical component, it is also useful to consider

some further descriptive analysis of the data. Consider first a brief exploration that looks at the number of courses of treatment that each patient has in the sample. This is presented in Table 5.5 below, with the distribution plotted in Figure 5.8 which follows.

Table 5.5: The Number of Courses of Treatment per Patient

Courses of Treatment per Patient	Number of Patients	%	Probability of Radiograph
1	20,841	25.98	0.305
2	10,971	13.67	0.284
3	8,204	10.23	0.256
4	6,888	8.58	0.228
5	6,164	7.68	0.213
6	5,488	6.84	0.192
7	5,041	6.28	0.176
8	4,585	5.71	0.159
9	3,869	4.82	0.148
10	2,757	3.44	0.147
11	1,807	2.25	0.155
12	1,141	1.42	0.154
13	729	0.91	0.144
14	537	0.67	0.150
15	356	0.44	0.150
16	255	0.32	0.149
17	158	0.20	0.134
18	126	0.16	0.142
19	101	0.13	0.132
20	72	0.09	0.119
21	42	0.05	0.118
22	30	0.04	0.095
23	20	0.02	0.126
24	18	0.02	0.137
25	11	0.01	0.182
26	5	0.01	0.215
27	3	0.00	0.148
28	6	0.01	0.244
29	2	0.00	0.224
30	1	0.00	0.133
31	2	0.00	0.032
32	1	0.00	0.156
35	1	0.00	0.000
36	1	0.00	0.028
38	1	0.00	0.342
Total	**80,234**	**100.00**	

Figure 5.8: The Number of Courses of Treatment per Patient

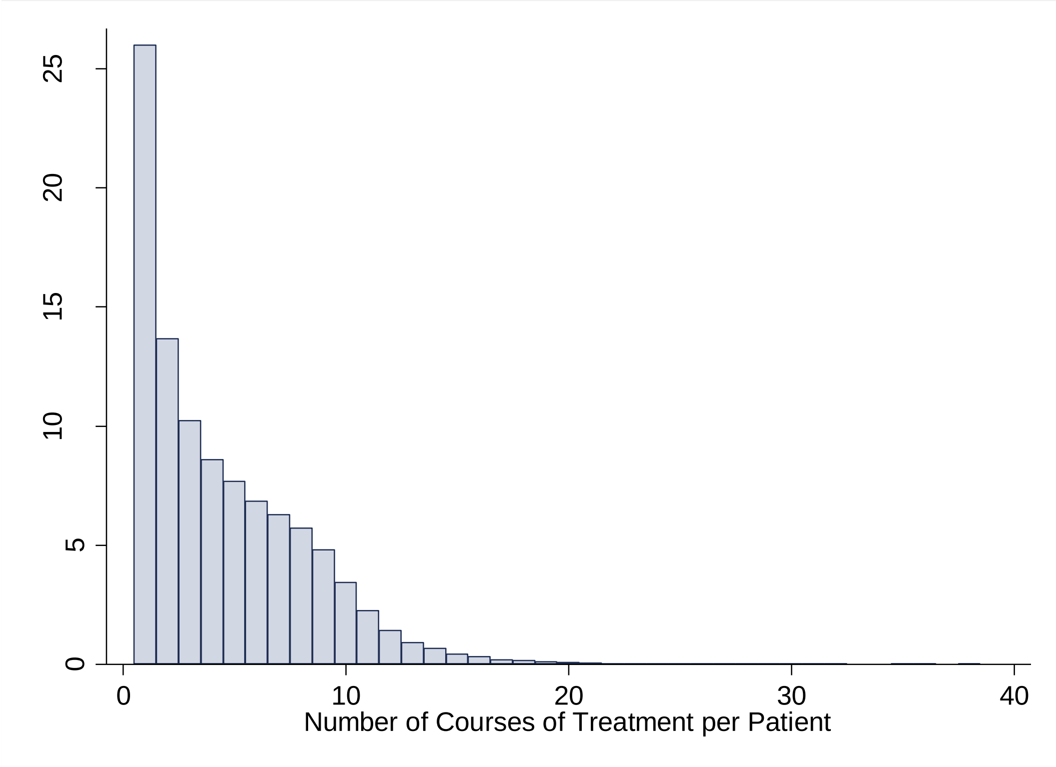


Table 5.5 and Figure 5.8 show that the number of courses of treatment (CoT) per patient ranges from 1 to 38. The average number of treatment claims per patient is 5 and just over 70% of the sample has 6 observations or less. Table 5.5 also shows the probability that on any given visit a patient is likely to receive a radiograph. These are given for all groups of patients with a particular number of observations in the sample. For example, patients with only 1 observation have on average, a 30% chance that they will be given a radiograph on any one visit to the dentist. In contrast, patients with 20 courses of treatment have only a 12% change of being provided with a radiograph. In general the results in Table 5.5 suggest that patients who visit the dentist more often (i.e. have more CoTs) in the sample are less likely to receive a radiograph. This appears to be up to a certain point (approximately 20 courses of treatment per patient) and then the trend almost

reverses. This could imply that if a patient is visiting a dentist often, there may be some clinical need for this which may warrant more radiographs. It is important to note that in some cases the low probabilities are due to the fact there is only 1 patient in the group.

Once the decision has been taken to attend a dentist, the next step is then to determine how many of these courses of treatment are likely to contain a radiograph. This information can be found in Table 5.6 and shows that the number of courses of treatment per patient containing a radiograph ranges from zero (for almost 50% of patients) to thirteen (for 2 patients in the sample).

Table 5.6: Courses of Treatment per Patient that Contained at Least One Radiograph

Courses of Treatment with Radiograph	Patients	%
0	37,897	47.23
1	25,490	31.77
2	10,263	12.79
3	4,006	4.99
4	1,581	1.97
5	611	0.76
6	248	0.31
7	76	0.09
8	36	0.04
9	10	0.01
10	9	0.01
12	5	0.01
13	2	0.00
Total	**80,234**	**100.00**

In order to look more closely at the factors that might influence a) the number of CoTs per patient (another way of thinking about it is number of visits to the dentist) and b) once at the dentist, the chances of being given a radiograph, methods which can model counts have to be used. Typically Poisson models are used to model count data, but here, negative binomial regressions are used. This is an extension to Poisson regression. It is less restrictive and can account for greater variation than Poisson variation as it does not rely on the assumption that every subject within a covariate has the same underlying rate of outcome. Two simple models are estimated. The first considers the factors that may influence the number of times a patient visits the dentist, the second then determines the factors that influence the number of treatments that contain at least one radiograph, whilst controlling for total number of visits. The results from both regressions are given in Table 5.7 below.

Table 5.7: Negative Binomial Regression Results

		No. of Visits		CoTs with Radiographs	
Variable	**Description**	**b**	**se**	**b**	**se**
page	Patient age	0.0096**	0.0002	-0.0153**	0.0003
psex	Patient sex (male=1)	-0.1428**	0.0055	0.4491**	0.0083
exempt	Equals 1 if patient is exempt	-0.1732**	0.0067	0.0119	0.0101
depcat	Deprivation category of the practice	-0.0303**	0.0018	0.0233**	0.0028
numobsp	Number of observations per patient	-	-	0.1339**	0.0010
cons	Regression Constant	1.3309	0.0115	-0.3504	0.0179

* Sig at 5% level; ** Sig at 1% level

The results from the first model (number of courses of treatment per patient) show that all coefficients are significant and suggest that older people are slightly more likely to have more visits to the dentist. Males and those who are exempt from the patient charge are less likely to have visits to the dentist, as are those patients who attend dental practices in areas of higher deprivation.

The results from the second regression (number of courses of treatment containing a radiograph) show that older patients are less likely to receive a radiograph. Males are more likely to be given them and those patients who are exempt from charges are also more likely to be given a radiograph, though the coefficient is not significant at the 5% level. The more courses of treatment that a patient has also increases their chance of being given a radiograph and patients who attend dental practices in more deprived areas are also more likely to receive radiographs.

The short descriptive analysis given above helps to gain a broad overview of some of the factors that might have an impact on the likelihood of receiving a radiograph, particularly at the very beginning of the decision process. It is useful to have some insight into the factors that actually impact on whether the patient visits their dentist often or not and to this to keep in mind when progressing to the much more complex empirical specifications presented in the next section.

5.3 Empirical Analysis

5.3.1 Regression Methods

As discussed in detail in the Introduction Chapter, the aim of this study is to investigate the variation in, and the determinates of the provision of dental radiographs across GDS dentists in the Scottish NHS, with a view to being able to identify and quantify the sources of this variation. Empirically this means estimating models that can account and control for factors that may influence the likelihood of a patient receiving a radiograph. These factors are discussed in detail in Chapter 3 (section 3.5.2) and show that it will depend on the individual characteristics and circumstances of the patient and the dentist. Practice characteristics may also be important. Many of these factors will be observable and can be estimated quite easily, for example standard age and gender controls, the contract of the dentist and the cost sharing element for patients through the exemption state category. There will, however, also be the unobservable characteristics that are important and need to be considered, but may not be as easily estimated. Unobserved patient heterogeneity exists because patients can be seen as being of different ‘types’. Some may have aversions to going to the dentist and may be more cautious about being exposed to radiation. On the other hand, some patients may be of the belief that radiographs are a good way of ensuring they are getting the best possible treatment and therefore expect a radiograph. In the case of the dentist the unobserved heterogeneity may come down to what is known as ‘practice style’, which simply means that different dentists have different inherent preferences in their methods of treatment. This could be as a result of where/how they trained, due to habit, or the influence of a particular working environment.

The decision as to which empirical methods should be adopted to aid answering the empirical question is usually highly dependent upon the data available. In this case the available data is a rich, highly functional, individual level dataset considered to be analogous to a matched patient provider dataset, similar to those described back in Chapter 3. Following on from this discussion, it should therefore be possible to apply similar methods and techniques. The structure of the dataset allows the application of panel data methods, where it should be possible to control for both patient and dentist unobserved heterogeneity. A key factor in this investigation is to be able to consider the variation at the dentist and patient levels, and where possible, both levels combined.

5.3.2 Model Specifications

The discussion presented in Chapter 3 described the development of a model by Andrews et al (2006) that could be used with matched data, and could incorporate both dentist and patient unobserved individual characteristics. Following this method, a general model of the following form is estimated:

$$\boldsymbol{y_{ik} = \mu + \mathrm{x}_{ik}\beta + \mathrm{u}_{jk}\gamma + \mathrm{w}_{ik}\eta + \mathrm{z}_{jk}\rho + \delta\big(\mathrm{w}_{ik}.\,\mathrm{z}_{jk}\big) + U_{ik}} \qquad \textbf{(5.3.1)}$$

where

$$U_{ik} = \alpha_i + \phi_j + \varepsilon_{ik}$$

Patients are indexed i = 1,...., N. They are observed once per course of treatment (CoT) k = 1,…, K_i provided by dentist j = 1,…, J. Patients can receive treatment from different dentists and the function $J(i,k)$ maps patient i to dentist j for CoT k.[42] In equation (5.3.1) y_{ik} is the probability of patient i receiving a radiograph on their kth course of treatment; x_{ik} is a set of observable explanatory variables that vary across patients and the patients different courses of treatment; u_{jk} is a set of observable explanatory variables that vary across dentists and different courses of treatment; z_{jk} is the remuneration contract of the dentist (which varies across observations for 39 dentists who switch contracts); w_{ik} is the exemption status of the patient (which varies for 10,119 patients who switch between exempt and non-exempt); and $\mathrm{w}_{ik}.\mathrm{z}_{jk}$ represents the interaction between dentist contract and exemption status. This term has been included to infer how the effect of the contract type on the probability of getting a radiograph might depend on the exemption status

[42] Rather than use the mapping function in the equation subscripts, the same approach as Andrews et al. (2006) is adopted. For more information refer back to section 3.5.3.

of the patient. It should help identify the true/full impact of dentist contract on y_{ik}. The error term, U_{ik} is made up of a patient specific effect (α_i), a dentist specific effect (ϕ_j) and the usual random error (ε_{ik}).

It is useful to highlight the difference between this specification and that used by Andrews et al. (2006). In the Andrews model the estimation was on workers in firms at different points in time. In this model dentists replace firms, patients replace workers and course of treatment replaces time. Whilst the Andrews model had workers in firms over time, this specification has patients receiving radiographs from dentists over a number of courses of treatment (which are occurring over time). Although a time variable as such is not included in this model specification, in order to take account of the influence of time on the probability of providing a radiograph, a variable that measures the time that has elapsed from a patient's last visit is included. It is believed that this should help capture any influence that time may have, for example is it more likely for a patient to receive a radiograph if it has been a long time since their last visit to the dentist? A further variable, *sdr*, has also been included in the regression model to try and capture any time effects. This is a dummy variable that represents a change to the Statement of Dental Remuneration, in relation to the fees that dentists can claim for any given item of treatment. It may be the case that an increase in the fee for a radiograph may result in a change in the likelihood that a dentist will provide one. The inclusion of the *sdr* variable should help control for these factors.

To consider fully the determinants of the provision of dental radiographs and the potential sources of variation in their use, it is necessary to estimate a range of specifications of the general model depicted in Equation (5.3.1). In order to make an informed decision about these particular specifications and what they can and should look like, a number of key questions need to be addressed. One of the most important will be the choice between linear and non-linear specifications, but also the way in which to account and control for the unobserved factors (both dentist and patient) needs to be considered. In order to conduct as complete a study as possible, both linear and non-linear models were considered (and estimated where possible), as were both random and fixed effects models, where the unobserved heterogeneity could be treated differently.

After careful consideration and a review of the literature it was decided that the model specifications to be estimated would take the linear form. There are a number of reasons for this decision, but the overwhelming one was due to the fact that it would not be possible to construct a non-linear model that could account for both dentist and patient unobserved heterogeneity simultaneously. It is possible to estimate non-linear models that could account for either dentist characteristics alone or patient characteristics alone, however not both together. There would then be a choice between random and fixed effects models, both of which present their own problems. There has been much debate about this choice, and it is clear there are advantages and disadvantages associated with both methods. Often the choice is based on how the researcher views the individual time-invariant components i.e. are they best viewed as being outcomes of a random variable or best viewed as parameters to be estimated. If the observations cannot be considered to be random draws from a large population, it might make more sense to think of the error components as parameters to be estimated and hence fixed effects estimation. The data and the particular empirical questions being addressed may also influence the decision on which might be the preferred model. For example, if it can be assumed that the unobserved individual effects are correlated with the explanatory variables, fixed effects estimation is required. Random effects estimation in this situation would result in inconsistent estimates. Fixed effects however may not be the most appropriate method if the aim of an analysis is to recover estimates of coefficients on time-invariant variables, both observed and unobserved. One aspect of this particular study is to address this shortcoming of the fixed effects model, and the methods described in section 3.2.4.4 do enable a fixed effects framework to be used and for all estimates of interest to be recovered in the process.

In making the choice between either fixed or random effects models, the Hausman test can be used to test for correlation between the random effects and the explanatory variables. The test is based on the idea that under the hypothesis of no correlation, both random and fixed effects models will give consistent estimates, however fixed effects estimation will be inefficient. Alternatively, when there is correlation, fixed effects models remain consistent, however random effects models will be inconsistent. This means that under the null hypothesis of no correlation, the two estimates would not be systematically different.(Greene 2002) The Hausman test essentially is based on any difference between the two estimators and if the null hypothesis can be rejected (i.e. reject the fact there is no correlation), then the fixed effects approach is preferred.

The underlying assumptions associated with random effects models, with regard to the correlation of unobserved heterogeneities with explanatory variables, represents a very strong assumption for the scenario being addressed here. In the case of fixed effects non-linear models, although estimable, the results are inconsistent. There is scope for further problems with non-linear models when it comes to the interpretation of coefficient results on interaction terms (Ai & Norton 2003).

In light of these factors, this study concentrates on a linear approach. However it is important to remember that there are a number of problems, well documented in the literature[43], with estimating linear probability models. Predicted probabilities can lie outside the unit interval and the model violates one of the Gauss-Markov (GM) assumptions. Gauss Markov theory states that under 5 certain assumptions, the OLS estimators are BLUE i.e. the best linear unbiased estimators, however if any of these assumptions do not hold the estimator may not be the most appropriate.[44] In the case of the linear probability model the GM assumption concerning the variance of the disturbance term is violated i.e. the variance of the disturbance/random component is not constant. This is referred to as heteroskedasticity and although it does not impact on the parameter estimates, it will bias the variance of the estimated parameters and thus affect the standard errors. It has however been shown that the linear probability model can still be useful and works well for values of the independent variables that are near the averages in the sample (see Wooldridge, 2002a). In this analysis prediction is not central; we are more concerned with the *ceteris paribus* effect of key variables on the probability of getting a radiograph. The standard errors can also be corrected to account for heteroskedasticity and clustering at the dentist and patient levels. It is important to remember that the main focus of the analysis is to be able to account in a general

[43] See for example Greene (2002); Johnston & Dinardo (1996); Wooldridge (2002b)
[44] For more detail on Gauss Markov theory, refer to Wooldridge (2002a), pp103-105

way for both patient *and* dentist individual effects, thus making the linear approach, despite its problems, the more favourable option.

For all specifications that follow, the interpretation of the coefficients on the regression variables is the same i.e. $[\beta,\gamma]$ is a vector of parameter estimates for observable dentist and patient characteristics, η is the effect of exemption status on the probability of getting a radiograph or not, for salaried dentists, ρ is the effect of contract type on the likelihood of a patient receiving a radiograph for non-exempt patients. δ is a difference in difference estimator and captures the difference in the impact on the probability of getting a radiograph due to exemption status for self employed dentists, compared to the impact due to exemption status for salaried dentists. Alternatively it could also be viewed as the change in the probability of getting a radiograph due to contract type for exempt patients compared to the probability due to contract type for non-exempt patients. If positive, this would mean that the impact of contract type on the probability of giving a radiograph is greater if patients are exempt, compared to non-exempt patients. Similarly it could also mean that the impact of exemption status on the chances of getting a radiograph is greater for self employed dentists, compared to salaried dentists, which might suggest that self employed dentists may be more likely to give exempt patients a radiograph than their salaried counterparts.

To begin, a simple OLS estimate of equation (5.3.1) provides a useful benchmark. A non-linear equivalent (probit) is also estimated for comparison. These specifications do not explicitly control for the individual patient and dentist specific effects; they are subsumed within the error term. It is assumed that this is uncorrelated with the explanatory variables of the model. A series of models that consider the dentist and patient specific effects separately are then estimated. In this analysis it is likely that the dentist (ϕ_j) and patient (α_i) specific effects will be correlated with some of the explanatory variables, and therefore fixed effects models are considered first. These treat both (ϕ_j) and α_i as separate parameters to be estimated. The following versions of equation (5.3.1) are estimated:

$$y_{ik} = \mu + \phi_j + \mathrm{x}_{ik}\beta + \mathrm{u}_{jk}\gamma + \mathrm{w}_{ik}\eta + \mathrm{z}_{jk}\rho + \delta(\mathrm{w}_{ik}.\mathrm{z}_{jk}) + \varepsilon_{ik} \qquad \textbf{(5.3.2)}$$

$$y_{ik} = \mu + \alpha_i + \mathrm{x}_{ik}\beta + \mathrm{u}_{jk}\gamma + \mathrm{w}_{ik}\eta + \mathrm{z}_{jk}\rho + \delta(\mathrm{w}_{ik}.\mathrm{z}_{jk}) + \varepsilon_{ik} \qquad \textbf{(5.3.3)}$$

It is also assumed that the unobserved dentist characteristics affect the likelihood of giving a radiograph in the same way across all patients. Similarly it is assumed that the unobserved patient effect is the same across dentists and courses of treatment. This is essentially assuming that both dentists and patients are of a particular 'type'. The fixed effects are identified because we have multiple observations on both dentists and patients.[45]

Random effects models assume that the unobserved heterogeneities are uncorrelated with all explanatory variables. This is a strong assumption, however given that they do provide more efficient estimates; models of this type are also estimated. These specifications treat ϕ_j and α_i as part of the error term. A Hausman test can then be run to compare with the fixed effects models.[46]

Finally, and the main focus of the analysis, a series of multi-level or 3-way error component models are estimated. These are models that can estimate the average effect associated with any dentist/patient characteristic, or any interaction of

[45] Although the multiple observations enable these effects to be identified from this data, it should be noted that in the case of patients they may not be well determined. This is due to the limited sample size for each patient.
[46] For more details of the Hausman specification test see J. A. Hausman (1978)

these characteristics, in the presence of, and accounting for, unobservable dentist and patient heterogeneity. Abowd & Kramarz (1999a) and Abowd, Kramarz & Margolis (AKM) (1999), discuss the potential biases that can arise from ignoring, in their case, either personal or firm heterogeneity. They propose that omitting either of these effects will result in an omitted variable bias equal to what they term the person-average firm effect and firm-average person effect, respectively. Applying the same logic to this analysis and considering dentist and patient effects, this means that omitting the patient effect would give a dentist effect that was made up of the pure dentist effect, but also an effect that measures the extent to which the average patient of a dentist deviates from the population of potential patients. In other words, what is the effect of heterogeneous patients on the composition of dentists' patient lists? Do some dentists simply end up with sets of patients that are just very different from the average patient? Abowd et al (1999b) propose that this effect will not be picked up unless the patient effects are also included in the analysis. Similarly, the same is true in the case of the patient effects when dentist effects are not included. A further aim of this analysis is therefore to investigate the existence and extent (if any) of such bias.

Three different multilevel specifications are estimated. Firstly a model that treats both the dentist and patient heterogeneity as random effects is considered. Then a model that treats both effects as fixed is estimated and finally a model that treats the dentist heterogeneity as fixed and the patient heterogeneity as random is considered. The specification that includes both heterogeneities as fixed effects presents some complications in estimation, much of which is discussed in AKM (1999) and Andrews et al (2006). AKM show that there are many common methods of approximating the solution, whilst Andrews et al (2006) present a more practical paper and show how the methods discussed in AKM can be implemented.[47] This study adopts the approach set out by Andrews et al (2006) and Cornelissen (2008a; 2008b) to estimate the 3-way error components model, where both the unobserved dentist and patient effects are treated as fixed effects.

5.3.3 Identification

Given the types of models being applied in this study, a key phenomenon to consider is that of identification. The overall focus of this particular investigation is to try and identify potential sources to explain the variation exhibited in the use of dental radiographs. These sources can stem from the usual economic incentives that often exist in a health care setting, e.g. the impact of dentist remuneration contracts and demand side cost sharing, but could also be the result of individual characteristics of either dentists or patients or potentially dentists and patients. In the latter case, in order to fully capture this, there has to be mobility in the sample. For example, if all patients received treatment from the same dentist each time over the sample period, the patient and dentist effects could not be identified separately. Thus in this case identification will only be possible if there is movement of patients between providers[48]. Table 5.8 below presents data on the mobility of patients in the sample period. Of the 80,234 distinct patients in the sample, just fewer than 70% were treated by one dentist; therefore about 30% (approx 25,000 patients) of the patients in the sample are mobile. Although the majority of patients don't switch between dentists, the key is that 'some' do.

[47] For full details refer to Chapter 3 - Empirical Methods
[48] For more information on identification see Abowd et al. (2002), *Computing person and firm effects using linked longitudinal employer-employee data.*

Table 5.8: The Number of Dentists per Patient

Dentist per patient	CoTs	%	Patients	%
1	201979	55.38	54581	68.03
2	102415	28.08	17818	22.21
3	41163	11.29	5711	7.12
4	13323	3.65	1569	1.96
5	4360	1.20	434	0.54
6	992	0.27	85	0.11
7	294	0.08	24	0.03
8	137	0.04	9	0.01
9	28	0.01	1	0.00
10	38	0.01	2	0.00
Total	**364729**	**100**	**80234**	**100**

At this point, it is useful to consider the group of patients who are classified as movers (i.e. they are treated by at least two dentists over the sample period) and see if they are any different from those who don't move (i.e. those treated by the same dentist throughout). Table 5.9 below presents the descriptives for these two groups of patients.

These stats alone suggest that there is no real difference between those patients who change dentists in the sample and those who have been seen by the same dentist. Consider some of the key variables; movers are more likely to be exempt from the patient charge and are more likely to receive a radiograph that non movers.

In particular, movers are more likely to receive a radiograph straight after a move (27% change of receiving a radiograph) compared to those patients who saw the same dentist as the previous visit (15% chance of being given a radiograph). In general most other variables are similar across the two groups of patients.

I calculated simple t-tests to compare the means across groups. These implied that the means of all variables (with the exception of orthodontic and trauma treatment) were statistically different between movers and non movers. Given the similarities of the means, these tests are most likely being pushed to statistical significance by the large sample size. However, I would be reluctant to conclude that there are economically significant differences between patients who move and those who don't given the very small differences in means.

Table 5.9: Descriptive Statistics for Movers & Non Movers

		Mover			Non-Mover		
Variable	**Description**	**Obs**	**Mean**	**Std. Dev**	**Obs**	**Mean**	**Std. Dev**
radiographs (code2a1)	Equals 1 if radiographic examination carried out	162750	0.21	0.41	201979	0.18	0.38
prev	dummy variable = 1 if this course involved preventative care	162750	0.00	0.02	201979	0.00	0.02
perio	dummy variable = 1 if this course involved peridontal treatment	162750	0.52	0.50	201979	0.56	0.5
cons	dummy variable = 1 if this course involved conservative treatment	162750	0.45	0.50	201979	0.39	0.49
surg	dummy variable = 1 if this course involved surgical treatment	162750	0.09	0.29	201979	0.08	0.27
prosth	dummy variable = 1 if this course involved prostheses, obturators and other (non-orthodontic) appliances	162750	0.08	0.26	201979	0.08	0.27
ortho	dummy variable = 1 if this course involved orthodontic treatment (major corrective work)	162750	0.00	0.04	201979	0.00	0.02
incomplete	dummy variable = 1 if this course of treatment was not completed prior to the claim being made	162750	0.01	0.09	201979	0.00	0.07
trauma	dummy variable = 1 if the claim is characterised by trauma	162750	0.00	0.02	201979	0.00	0.02
depcat	Deprivation category of the practice (1=least deprived, 7=most deprived)	162750	3.87	1.57	201979	3.82	1.49
dage	Dentist age	162750	38.16	10.12	201979	41.94	9.02
dsex	Dentist sex (male=1)	162750	0.67	0.47	201979	0.78	0.41
se	Contract type of Dentist (=1if self-employed, 0 if salaried)	162750	0.98	0.14	201979	0.99	0.12
clpery	Claims per dentist per year	162750	63.18	31.32	201979	72.24	32.44
page	Patient age	162750	43.93	14.17	201979	44.61	14.71
psex	Patient sex (male=1)	162750	0.42	0.49	201979	0.44	0.5
exempt	Equals 1 if patient is exempt	162750	0.28	0.45	201979	0.24	0.42
numobsp	Number of observations per patient	162750	8.44	4.30	201979	6.66	4.02
lastvisit	Time since last visit (months)	137552	7.42	6.77	149291	7.73	5.78

Similarly for contract effects to be separately identified from individual effects there has to be mobility of both dentists and patients between contract types. In other words some dentists will have to have worked as both self employed and salaried dentists at some point during the sample period. Likewise some patients will also have to have moved between dentists working under different contractual arrangements, if the impact of the contract per patient is to be identified.

Table 5.10 reports that of the 2377 distinct dentists in the dataset, 2238 (94.15%) are always self employed, with only 39 (1.6%) having worked under both contracts.

Table 5.10: The Number of Dentists by Contract Type over the Sample Period

Contract Type	CoTs	%	Dentists	%
self employed only	355564	97.49	2238	94.15
salaried only	4717	1.29	100	4.21
self employed & salaried	4448	1.22	39	1.64
Total	**364729**	**100**	**2377**	**100**

Given that the contract effects are identified in the model through those who change contracts, it is also worth investigating whether there is some difference between dentists who switch contract and dentists who remain on the same payment contract during the course of the sample period. Table 5.11 below presents some descriptive stats, for each dentist group, i.e. always self-employed, always salaried, and then those who have worked as both.

The descriptives for dentists who change contract versus those who haven't, like the movers versus non movers, suggest there is little difference between them. Again consider some of the key variables of interest. Dentists who switch contract may be slightly less likely to provide a radiograph compared to those who are always salaried and always self employed as 17% of their claims contained a radiograph, compared to 19% of claims by self employed and salaried dentists. They also appear to treat less exempt patients, 23% of claims were for those who were exempt, compared to 25 and 26% of claims for salaried and self employed dentists respectively.

Table 5.11: Descriptive Stats for Dental Contracts

		Always self-employed		Always salaried		Switch Contract	
Variable	**Description**	**Obs**	**Mean**	**Obs**	**Mean**	**Obs**	**Mean**
radiographs (code2a1)	Equals 1 if radiographic examination carried out	355564	0.19	4717	0.19	4448	0.17
prev	dummy variable = 1 if this course involved preventative care	355564	0.00	4717	0.00	4448	0.00
perio	dummy variable = 1 if this course involved peridontal treatment	355564	0.55	4717	0.39	4448	0.39
cons	dummy variable = 1 if this course involved conservative treatment	355564	0.42	4717	0.36	4448	0.41
surg	dummy variable = 1 if this course involved surgical treatment	355564	0.87	4717	0.12	4448	0.08
prosth	dummy variable = 1 if this course involved prostheses, obturators and other (non-orthodontic) appliances	355564	0.08	4717	0.08	4448	0.07
ortho	dummy variable = 1 if this course involved orthodontic treatment (major corrective work)	355564	0.00	4717	0.00	4448	0.00
incomplete	dummy variable = 1 if this course of treatment was not completed prior to the claim being made	355564	0.01	4717	0.00	4448	0.01
trauma	dummy variable = 1 if the claim is characterised by trauma	355564	0.00	4717	0.00	4448	0.00
depcat	Deprivation category of the practice (1=least deprived, 7=most deprived)	355564	3.85	4717	3.77	4448	3.40
dage	Dentist age	355564	40.22	4717	44.94	4448	37.94
dsex	Dentist sex (male=1)	355564	0.73	4717	0..71	4448	0.63
se	Contract type of Dentist (=1if self-employed, 0 if salaried)	355564	1.00	4717	0.00	4448	0.64
clpery	Claims per dentist per year	355564	68.94	4717	31.73	4448	47.47
page	Patient age	355564	44.33	4717	44.47	4448	42.72
psex	Patient sex (male=1)	355564	0.43	4717	0.44	4448	0.44
exempt	Equals 1 if patient is exempt	355564	0.26	4717	0.25	4448	0.24
numobs	Number of observations per dentist	355564	266.74	4717	112.86	4448	161.29
lastvisit	Time since last visit (months)	280637	7.55	3088	9.94	3118	8.14

There was little difference across demographic variables and treatment category variables, perhaps with the exception of the provision of periodontal treatment (where salaried dentists and those who switch contract have less claims with this type of treatment in it) and surgical treatment (where those who were always salaried have more claims with surgical treatment than the other groups).

Salaried dentists also appear to treat patients that attend the dentist less often given that on average the length of time between visits is 10 months for claims made by salaried dentists, compared to approximately 8 months for the other groups of dentists.

I performed a similar comparison to that of the movers and non movers and used a one way anova to compare the means of the variables across the three different groups. This also produced similar results, suggesting that the means across groups are statistically different from one another. However, again, given the small differences in magnitude of the means, I think it is likely that there will be little difference between the different groups of dentists in terms of the impact of changing contracts.

Table 5.12 below shows that only 820 (1%) patients were treated by both self employed and salaried dentists.

Table 5.12: The Number of Patients Treated by Dentists with a Given Contract

Contract Type	CoTs	%	Patients	%
self employed only	355845	97.56	77570	96.68
salaried only	4582	1.26	1844	2.30
self employed & salaried	4302	1.18	820	1.02
Total	**364729**	**100**	**80234**	**100**

Finally, the impact of the demand side cost sharing (exemption) effects can only be identified if there is patients in the sample that switch between exemption states throughout the period. If not, it would not be possible to separate them from individual patient specific effects. Table 5.13 shows that 12.61% of patients were both exempt and non-exempt at times throughout the sample period.

Table 5.13: The Number of Patients by Exemption Status

Exemption Status	CoTs	%	Patients	%
Non exempt only	237015	64.98	50502	62.94
exempt only	67181	18.42	19613	24.44
exempt & non exempt	60533	16.60	10119	12.61
Total	**364729**	**100**	**80234**	**100**

The issues regarding identification discussed here relate to the models in which both individual patient and dentist heterogeneity is being controlled for. It is also worth noting the impact of mobility on the precision of the estimates of the dentist effects[49]. The estimates are more precise the more movers there are per dentist in the sample. The estimates of the patient effects are a function of the number of observations per patient. This is similar to the case when only one level of heterogeneity is being considered. In this instance the effects are identified due to the panel nature of the data, where there are multiple observations on both dentists and patients, thus making the precision of the estimated effects dependent on the number of observations per patient or dentist.

5.3.4 Empirical Results

The subsections that follow present and discuss the results from the empirical analysis.

[49] For further discussion of the accuracy of the results please see pages 165-167

5.3.4.1 General

The results of estimating 9 specifications of Equation 5.3.1 are given in Table 5.14[50]. The sets of results that have been highlighted will be discussed in greater detail in the next section (5.3.4.2). All model specifications are estimated with robust standard errors to take account of any heteroskedasticity and to account for any clustering at the patient and dentist levels. Models 1 and 2 are the simplest form and do not explicitly control for the unobserved heterogeneity. The OLS estimate is used only to provide a benchmark for the models that follow. The adjusted R^2 from the OLS estimate suggests that approximately 9% of the variation in radiograph use across GDS dentists is explained by the model. The probit model (column 2 in Table 5.14) is estimated to provide a non-linear comparison to the general OLS, in attempt to gauge the extent of any difference between the two. It is useful to point out that relatively little difference exists. The direction of all variables in each model are the same, as to is the level of significance, with the exception of a couple of deprivation category dummies (depcat_5 and _6 are significant in the probit model but not in the OLS) and one sdr dummy (sdr_7 is significant under OLS, but not in the probit model). The magnitude of the coefficients and standard errors are also very similar.

[50] Standard errors in parentheses; * denotes significant at the 5% level and $^+$ denotes significant at the 10% level.

Table 5.14: Regression Results

Variable	1 OLS	2 Prob	3 FE j	4 RE j	5 FE i	6 RE i	7 RE i RE j	8 FE i FE j	9 RE i FE j
	b/se	(dF/dX)/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
prev	0.0801*	0.0717*	0.0564	0.057	0.0658	0.0748*	0.0556+	0.0581	0.0554
	[0.0358]	[0.0372]	[0.0369]	[0.0366]	[0.0439]	[0.0366]	[0.0324]	[0.0448]	[0.0356]
perio	0.0150*	0.0099*	0.0035+	0.0048*	0.0098*	0.0143*	0.0055*	0.0060*	0.0050*
	[0.0015]	[0.0015]	[0.0020]	[0.0020]	[0.0020]	[0.0016]	[0.0015]	[0.0020]	[0.0016]
cons	0.1570*	0.1576*	0.1555*	0.1559*	0.1330*	0.1509*	0.1543*	0.1320*	0.1511*
	[0.0016]	[0.0016]	[0.0024]	[0.0024]	[0.0019]	[0.0016]	[0.0014]	[0.0019]	[0.0016]
surg	0.2091*	0.2322*	0.2098*	0.2096*	0.2050*	0.2066*	0.2088*	0.2052*	0.2080*
	[0.0034]	[0.0040]	[0.0049]	[0.0049]	[0.0040]	[0.0034]	[0.0026]	[0.0039]	[0.0034]
prosth	-0.0354*	-0.0471*	-0.0401*	-0.0396*	-0.0009	-0.0274*	-0.0374*	-0.0025	-0.0326*
	[0.0027]	[0.0141]	[0.0030]	[0.0030]	[0.0036]	[0.0028]	[0.0028]	[0.0036]	[0.0028]
ortho	-0.0933*	-0.1283*	-0.0158	-0.0839*	-0.0474*	-0.0887*	-0.0885*	-0.0106	-0.0169
	[0.0079]	[0.1967]	[0.0174]	[0.0101]	[0.0215]	[0.0085]	[0.0237]	[0.0303]	[0.0164]
incomplete	0.2358*	0.2380*	0.2169*	0.2188*	0.1694*	0.2144*	0.2152*	0.1582*	0.2032*
	[0.0121]	[0.0340]	[0.0128]	[0.0128]	[0.0137]	[0.0119]	[0.0090]	[0.0136]	[0.0118]
trauma	0.1032*	0.1058*	0.1003*	0.0987*	0.1135*	0.1078*	0.1009*	0.1098*	0.1030*
	[0.0346]	[0.1086]	[0.0328]	[0.0328]	[0.0377]	[0.0346]	[0.0270]	[0.0372]	[0.0338]
caid_1	-0.0837*	-0.0674*	-0.6868*	-0.0493+	-0.1264	-0.0773*	-0.0509	-0.8364*	-0.7101*
	[0.0141]	[0.0530]	[0.0438]	[0.0255]	[0.1025]	[0.0143]	[0.0321]	[0.2019]	[0.0496]
caid_2	-0.0755*	-0.0624*	-0.6299*	-0.0314	-0.2367*	-0.0691*	-0.034	-0.8726*	-0.6517*
	[0.0145]	[0.0561]	[0.0899]	[0.0304]	[0.1041]	[0.0147]	[0.0340]	[0.2153]	[0.0613]
caid_3	-0.0742*	-0.0612*	-0.7065*	-0.0463+	-0.1009	-0.0663*	-0.0459	-0.8674*	-0.7329*
	[0.0141]	[0.0529]	[0.0438]	[0.0259]	[0.1013]	[0.0143]	[0.0320]	[0.2001]	[0.0488]
caid_4	-0.0906*	-0.0739*	-0.7033*	-0.0625*	-0.12	-0.0840*	-0.0632*	-0.8375*	-0.7253*
	[0.0141]	[0.0530]	[0.0418]	[0.0258]	[0.1026]	[0.0142]	[0.0322]	[0.2019]	[0.0492]

Variable	1 OLS	2 Prob	3 FEj	4 REj	5 FEi	6 REi	7 REiREj	8 FEiFEj	9 REiFEj
caid_5	-0.0476* [0.0141]	-0.0423* [0.0526]	-0.6719* [0.0421]	-0.0188 [0.0255]	-0.0907 [0.0999]	-0.0400* [0.0142]	-0.0185 [0.0319]	-0.8042* [0.1989]	-0.6953* [0.0481]
caid_6	-0.0717* [0.0147]	-0.0574* [0.0555]	-0.7003* [0.0060]	-0.0516* [0.0259]	-0.1399 [0.1089]	-0.0636* [0.0148]	-0.0516 [0.0325]	-0.8288* [0.1931]	-0.7222* [0.0295]
caid_7	-0.0771* [0.0141]	-0.0634* [0.0527]	-0.6766* [0.0433]	-0.0398 [0.0257]	-0.0977 [0.1004]	-0.0679* [0.0142]	-0.0413 [0.0320]	-0.8032* [0.1993]	-0.6992* [0.0487]
caid_8	-0.0819* [0.0141]	-0.0679* [0.0526]	-0.6755* [0.0436]	-0.0471+ [0.0256]	-0.133 [0.1018]	-0.0760* [0.0142]	-0.0483 [0.0321]	-0.8481* [0.2008]	-0.7012* [0.0451]
caid_9	-0.1459* [0.0202]	-0.1017* [0.1002]	-0.7385* [0.0441]	-0.1210* [0.0259]	-0.0443 [0.1436]	-0.1447* [0.0196]	-0.1223* [0.0418]	-0.6033* [0.2326]	-0.7635* [0.0555]
caid_10	-0.0614* [0.0140]	-0.0522* [0.0522]	-0.6906* [0.0413]	-0.0335 [0.0253]	-0.1018 [0.1007]	-0.0532* [0.0141]	-0.0333 [0.0318]	-0.8216* [0.1994]	-0.7122* [0.0478]
caid_11	-0.0706* [0.0141]	-0.0585* [0.0527]	-0.6483* [0.0433]	-0.0299 [0.0256]	-0.1305 [0.1020]	-0.0634* [0.0142]	-0.0322 [0.0321]	-0.8268* [0.2010]	-0.6742* [0.0485]
caid_12	-0.0519* [0.0143]	-0.0436* [0.0533]	-0.6598* [0.0456]	-0.0172 [0.0265]	0.0189 [0.1027]	-0.0439* [0.0144]	-0.018 [0.0325]	-0.7556* [0.2017]	-0.6860* [0.0503]
caid_13	-0.0636* [0.0186]	-0.0517* [0.0713]	-0.6849* [0.0437]	-0.0379 [0.0311]	-0.1226 [0.1415]	-0.0607* [0.0190]	-0.0393 [0.0399]	-0.9725* [0.2400]	-0.7181* [0.0673]
caid_14	-0.1019* [0.0146]	-0.0818* [0.0571]	-0.7839* [0.2204]	-0.0891* [0.0280]	-0.1522 [0.1075]	-0.0966* [0.0147]	-0.0889* [0.0342]	-0.8026* [0.2768]	-0.7843* [0.1454]
depcat_2	0.0056 [0.0037]	0.0043 [0.0157]	-0.0164 [0.0159]	-0.0009 [0.0089]	0.0453* [0.0164]	0.0096* [0.0038]	0.0013 [0.0074]	0.0256 [0.0235]	-0.0141 [0.0123]
depcat_3	-0.0029 [0.0036]	-0.0046 [0.0155]	-0.0217 [0.0169]	-0.0062 [0.0094]	0.0147 [0.0169]	-0.0001 [0.0038]	-0.0041 [0.0072]	-0.0026 [0.0237]	-0.0204+ [0.0122]
depcat_4	-0.0008 [0.0034]	-0.0031 [0.0147]	-0.0254 [0.0161]	-0.0069 [0.0088]	0.0277+ [0.0156]	0.003 [0.0035]	-0.0043 [0.0069]	0.0022 [0.0228]	-0.0216+ [0.0120]

Variable	1 OLS	2 Prob	3 FEj	4 REj	5 FEi	6 REi	7 REiREj	8 FEiFEj	9 REiFEj
depcat_5	-0.0047	-0.0066+	-0.0321+	-0.0146	0.0227	-0.0029	-0.0127+	-0.021	-0.0301*
	[0.0037]	[0.0157]	[0.0168]	[0.0093]	[0.0167]	[0.0038]	[0.0075]	[0.0241]	[0.0129]
depcat_6	-0.0062	-0.0081*	-0.0372*	-0.0157	0.003	-0.0052	-0.0132+	-0.0101	-0.0352*
	[0.0042]	[0.0172]	[0.0173]	[0.0099]	[0.0183]	[0.0043]	[0.0079]	[0.0273]	[0.0135]
depcat_7	-0.0099+	-0.0114*	-0.0264	-0.013	0.0465*	-0.0053	-0.0115	-0.0114	-0.0208
	[0.0051]	[0.0203]	[0.0226]	[0.0127]	[0.0235]	[0.0053]	[0.0091]	[0.0354]	[0.0163]
sdr_2	-0.0019	-0.0024	-0.0033	-0.0032	-0.0051	-0.0027	-0.0036	-0.0063	-0.0039
	[0.0047]	[0.0210]	[0.0048]	[0.0048]	[0.0051]	[0.0047]	[0.0047]	[0.0051]	[0.0047]
sdr_3	0.0025	0.0027	0.0016	0.0025	0.0024	0.0029	0.0026	0.0002	0.0014
	[0.0029]	[0.0127]	[0.0031]	[0.0030]	[0.0031]	[0.0029]	[0.0029]	[0.0032]	[0.0030]
sdr_4	0.0035	0.0034	-0.0004	0.0023	0.0045	0.0043	0.0024	-0.0002	-0.0001
	[0.0043]	[0.0185]	[0.0047]	[0.0044]	[0.0046]	[0.0043]	[0.0042]	[0.0050]	[0.0046]
sdr_5	-0.0011	-0.0010	-0.005	-0.0023	-0.0016	-0.0006	-0.0023	-0.006	-0.0051
	[0.0043]	[0.0189]	[0.0049]	[0.0046]	[0.0047]	[0.0043]	[0.0043]	[0.0050]	[0.0046]
sdr_6	0.0061	0.0061	0.0032	0.006	0.0102*	0.0079+	0.0062	0.0046	0.0038
	[0.0043]	[0.0184]	[0.0048]	[0.0045]	[0.0047]	[0.0043]	[0.0042]	[0.0050]	[0.0046]
sdr_7	0.0072*	0.0069	0.0019	0.0063+	0.0064+	0.0079*	0.0062*	-0.0007	0.0018
	[0.0032]	[0.0137]	[0.0044]	[0.0034]	[0.0036]	[0.0032]	[0.0032]	[0.0047]	[0.0043]
sdr_8	0.0063	0.0068	0.0005	0.0057	0.0068	0.0074	0.0057	-0.0008	0.0006
	[0.0055]	[0.0235]	[0.0067]	[0.0057]	[0.0061]	[0.0055]	[0.0054]	[0.0071]	[0.0065]
sdr_9	0.0043	0.0041	-0.0053	0.0014	0.0013	0.0048+	0.0013	-0.0091	-0.0055
	[0.0029]	[0.0125]	[0.0052]	[0.0031]	[0.0035]	[0.0029]	[0.0029]	[0.0056]	[0.0050]
sdr_10	0.0068*	0.0065+	0.0115*	0.0080*	0.0034	0.0055+	0.0077*	0.0063	0.0104*
	[0.0033]	[0.0144]	[0.0043]	[0.0034]	[0.0036]	[0.0033]	[0.0033]	[0.0044]	[0.0041]
sdr_11	-0.0047	-0.0049	-0.0002	-0.0029	-0.0037	-0.0048	-0.0029	-0.0011	-0.0005
	[0.0036]	[0.0157]	[0.0041]	[0.0036]	[0.0037]	[0.0035]	[0.0035]	[0.0042]	[0.0039]

Variable	1 OLS	2 Prob	3 FEj	4 REj	5 FEi	6 REi	7 REiREj	8 FEiFEj	9 REiFEj
sdr_12	-0.005	-0.0051	-0.0014	-0.0039	-0.0056	-0.0051	-0.0039	-0.0035	-0.0017
	[0.0036]	[0.0157]	[0.0039]	[0.0035]	[0.0038]	[0.0036]	[0.0036]	[0.0043]	[0.0039]
dage	-0.0018*	-0.0011+	0.0067+	-0.0004	-0.0001	-0.0019*	-0.0008	0.0003	0.0058+
	[0.0006]	[0.0028]	[0.0035]	[0.0015]	[0.0013]	[0.0007]	[0.0013]	[0.0034]	[0.0030]
dage2	0	-2.75e-06	-0.0001*	0	0	0	0	0	-0.0001*
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
dsex	-0.0084*	-0.0076*	0	-0.0129*	-0.0099*	-0.0093*	-0.0123*	0.9914	-0.3071*
	[0.0019]	[0.0077]	.	[0.0045]	[0.0041]	[0.0020]	[0.0043]	[72.4363]	[0.1285]
psex	-0.0039*	-0.0038*	-0.0042*	-0.0041*	0	-0.0027+	-0.0040*	0	-0.0036*
	[0.0016]	[0.0068]	[0.0015]	[0.0015]	.	[0.0016]	[0.0015]	.	[0.0015]
exempt	-0.0146	-0.0146	0.0054	0.0003	0.0151	-0.0121	-0.0016	0.0102	0.0048
	[0.0143]	[0.0603]	[0.0160]	[0.0158]	[0.0284]	[0.0145]	[0.0137]	[0.0292]	[0.0145]
se	0.0047	0.0060	-0.0009	0.0023	0.0225	0.0092	0.0042	-0.0178	-0.0071
	[0.0068]	[0.0298]	[0.0189]	[0.0109]	[0.0179]	[0.0070]	[0.0108]	[0.0369]	[0.0180]
seexempt	0.0225	0.0208	0.0048	0.0098	0.0075	0.0204	0.0115	0.0144	0.0056
	[0.0144]	[0.0608]	[0.0161]	[0.0159]	[0.0285]	[0.0146]	[0.0138]	[0.0293]	[0.0146]
lastvisit	0.0041*	0.0033*	0.0042*	0.0042*	0.0033*	0.0040*	0.0041*	0.0032*	0.0040*
	[0.0001]	[0.0005]	[0.0002]	[0.0002]	[0.0002]	[0.0001]	[0.0001]	[0.0002]	[0.0001]
clpery	-0.0004*	-0.0005*	-0.0002*	-0.0003*	-0.0003*	-0.0004*	-0.0003*	-0.0003*	-0.0002*
	[0.0000]	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0000]	[0.0000]	[0.0001]	[0.0001]
page	0.0007*	0.0019*	0.0013*	0.0012*	0.0057*	0.0011*	0.0013*	0.0038*	0.0014*
	[0.0003]	[0.0014]	[0.0003]	[0.0003]	[0.0018]	[0.0003]	[0.0003]	[0.0018]	[0.0003]
page2	-0.0000*	-4.39e-05*	-0.0000*	-0.0000*	-0.0001*	-0.0000*	-0.0000*	-0.0000*	-0.0000*
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
_cons	0.2493*	-0.7864*	0.6551*	0.2011*	0.0873	0.2412*	0.2080*	0.6298*	0.8006*
	[0.0218]	[0.0868]	[0.1044]	[0.0403]	[0.1130]	[0.0224]	[0.0424]	[0.2626]	[0.1622]

Variable	1 OLS	2 Prob	3 FEj	4 REj	5 FEi	6 REi	7 REiREj	8 FEiFEj	9 REiFEj
F	419.773		1.39E+11		168.247			325.479	
r2_o			0.069376	0.085056	0.069407	0.085663		0.061851	0.129037
r2_w			0.07489	0.074768	0.046	0.045012		0.069975	0.059777
r2_b			0.067921	0.217904	0.120537	0.165528		0.093857	0.252472
N	286843	286843	286843	286843	286843	286843	286843	286843	286843
N_g			2335	2335	60370	60370		60370	60370
g_avg			122.845	122.845	4.751416	4.751416		4.751416	4.751416
sigma_u			0.145385	0.088804	0.25675	0.125088		0.276972	0.102012
sigma_e			0.352358	0.352359	0.346194	0.346195		0.343566	0.343565
rho			0.145477	0.059724	0.354849	0.115477		0.393906	0.081019

Models 3 (FEj) and 4 (REj) are specifications that attempt to control for only unobserved dentist heterogeneity. Model 3 results are from the fixed effects specification and an F test that all dentist specific effects are 0 is rejected i.e. $\phi_{j(i,k)} = 0$: F (2334, 284459) = 6.13 Prob>F = 0.000. An F test that all explanatory variables are jointly equal to zero is also rejected. Model 4 treats the dentist specific effects as random. A χ^2 test shows that the coefficients are jointly significant i.e. χ^2 (50) = 8347.8 Prob> χ^2 = 0.000. This model is more efficient, though possibly inconsistent given the underlying assumptions about the error term and explanatory variables.

Rho (ρ) is a measure of the fraction of the variation in the error term that is due to the individual effects. In random effects models, these individual effects are estimated as part of the error term and can therefore give some indication of the proportion of the variation in radiographs that can be attributed to, in this case, the dentist effects. It shows that approximately 6% (ρ = 0.06) of the variation in the likelihood of getting a radiograph is accounted for by the dentist specific time invariant effects, say for example practice style. The interpretation of ρ in fixed effects models is more complicated as the estimates of the variance in individual effects can also be picking up the effects of any time invariant variables, so the ρ reported in the dentist fixed effects model cannot give a similar indication of the influence of individual effects on the overall variation.

A Hausman test is performed to compare the two specifications. This is a specification test that tests the difference in coefficients between the fixed and random effects models. In this case the hypothesis that coefficients are the same is rejected and the fixed effects model is preferred. If the no correlation assumption did hold then the subset of coefficients that are estimated by the fixed effects estimator and the same coefficients estimated by the random effects estimator would not statistically differ.[51]

Models 5 (FEi) and 6 (REi) are similar to models 3 and 4, with the difference being that these specifications now consider and control for only the unobserved patient heterogeneity. An F test that all patient fixed effects are equal to zero is rejected[52], as is an F test that all explanatory variables are equal to zero (F = 222.81). The random effects specification, model 6 shows that almost 12% of the variation in the chances of getting a radiograph can be accounted for by unobserved patient heterogeneity (ρ = 0.115). Again a Hausman test of the two specifications suggests that fixed effects are preferred.[53]

The multilevel or 3-way error components specifications, models 7-9 attempt to control for both unobserved dentist *and* patient heterogeneity. Model 7 (REiREj) treats both effects as random and includes them as part of the error term. The variance terms associated with both the dentist and patient random-effects parameters are significantly different from zero and suggest that dentist specific effects account for 7.8% of the variance in the error term and patient specific effects account for 6.2% of the variance. The remaining two specifications are estimated using the FEiLSDVj method, where dummy variables are included for each dentist. Model 8 (FEiFEj) treats the individual characteristics as fixed effects. F tests show the dentist and patient specific effects are both individually and jointly significantly

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[51] For more information on the Hausman specification test refer to Baltagi (2001) pp65-72

[52] α_i =0: F(60369, 226424) = 1.38 Prob>F = 0.000

[53] H_0: difference in coefficients is not systematic, χ^2 (45) = 768.15 Prob> χ^2 = 0.0000.

different from zero.[54] The results also give an indication of their importance in explaining the overall variation in the use of radiographs. They suggest that as much as 22.5% can be attributed to the patient fixed effects, whilst only 5.2% of the variation in radiograph provision is due to individual dentist fixed effects.[55] The final model also includes dummy variables for the dentists but treats the patient effects as random (REiFEj). It suggests that approximately 7% of the variation in the use of radiographs is accounted for by patient effects (ρ = 0.069).

This study aims to account for the variation in and the determinants of the use of radiographs across dentists in Scotland by trying to control for both observed and unobserved factors. There are two key observable factors to be considered, namely the contract type of the dentist and the exemption status of the patient at the time of treatment. The interaction between these two variables is also of interest. A summary of the remaining coefficients across the different model specifications is provided before considering these in more detail.

A number of broad treatment categories have been included in the regressions in order to try and take account of a patients underlying need for dental treatment or overall dental condition. They help to capture the influence of other treatments on the probability of getting a radiograph. It might be the case that patients with a greater need receive lots of different treatments and so are more likely to receive a radiograph. These variables in a sense try to control for different types of patients. The results show that on the whole, coefficients for the majority of the

[54] F-test that patient and dentist effects are equal to zero: F(62669, 224125) = 1.44 Prob> F = 0.000
F-test that patient effects are equal to zero: F(60368, 224125) = 1.24 Prob> F = 0.000
F-test that dentist effects are equal to zero: F(2300, 224125) = 2.51 Prob> F = 0.000

[55] These figures are obtained from estimating model 8 using Stata's felsdvreg command. This is simply a memory saving way to compute the FEiLSDVj estimates and give equivalent results. For more information see Cornelissen (2008a).

treatment categories, across all model specifications are significant. The main exception to this is in the case of preventative care, which although has the same sign and magnitude across models, the significance varies in no apparent pattern. Coefficient estimates on prosthetic and orthodontic are not significant in fixed effects models. Patients receiving these types of treatment are also less likely to receive a radiograph. Although this may at first sight seem odd, it could be that for these types of treatment, radiographs of a different/more complicated nature are required and not the most basic small film radiograph (code2a1), considered in this study.

The variables, caid1-caid14 are dummy variable indicators that give an indication as to the particular Health Board the dental practice belongs to, and hence can act as some geographical indicator. The coefficients on these give a measure of the probability of getting a radiograph in a practice within a particular health board, compared to being treated in a practice in health board 15 (the omitted category). The results show that in all models, patients treated in a practice residing in health board 15 are more likely to receive a radiograph than patients treated in practices in all other health boards, with the only single exception being in model 5 (FEi), where patients treated in health board 15 are less likely to receive a radiograph than patients being treated in health board 12. The magnitudes of the coefficients are larger in models that control for dentist and patient specific effects, with significantly larger estimates in model FEiFEj that controls for both. The estimates are mostly significant, though the standard errors are relatively large. It is difficult to draw any firm conclusions about this impact as the health boards are anonymous in the data sample, although given the trend that patients are always less likely to receive a radiograph compared to the reference group (health board 15), perhaps this could indicate that the reference is one of the larger boards with potentially more deprived areas.

The coefficients on the deprivation categories follow no obvious pattern across models. In most cases the results suggest that as the level of deprivation increases (moving from depcat 2-7) patients are less likely to receive a radiograph than those patients treated in practices residing in the least deprived area. However, the coefficients are small in magnitude and are in the most part not significant. The coefficient estimates change sign from being negative when dentist fixed effects are controlled for alone, to positive when just patient fixed effects are controlled. In other words once unobserved patient heterogeneity has been accounted for; patients treated in more deprived areas are more likely to receive a radiograph than those treated in the least deprived area. However when both patient and dentist fixed effects are included in the model (FEiFEj), the sign reverts back to negative.

The sdr dummies are included to capture changes that might occur over time as the statement of dental remuneration is revised, for example dentists' decisions may be influenced if the revisions impact on the magnitude of net marginal benefits. There is no set time at which these changes occur but in this sample they are at approximately 6 monthly intervals. The omitted category, sdr1 represents the fee scale in operation at the beginning of the sample period and all effects are relative to this. The coefficients on all sdr variables across all specifications are small and not significantly different from sdr1. The only exception to this is sdr10 where the coefficients are mostly significant across models, but still relatively small in magnitude. This might suggest that changes in the fee scale over time have had little impact on the likelihood of dentists giving and patients receiving radiographs.

Standard age and gender controls are also included to further account for different types of dentist and patient. In the case of patients, across all specifications that can estimate these[56], the age and gender controls (*page, psex*) are both significant and of similar magnitudes and directions. The results suggest that in general female patients are slightly more likely to receive a radiograph than their male counterparts. The chances of getting a radiograph increase with patient age, although at a decreasing rate. This chance will continue to increase up to around the age of 40-50 (dependent on the model specification), then decreases. The magnitude of this effect is greater in models that control for patient specific effects.

For dentists, again the results relating to gender are significant and suggest that female dentists are slightly more likely (approx 1%) to give radiographs than males. The results relating to dentist age suggest that the likelihood of giving radiographs is decreasing with age; however the results are not significant.

A final variable included in the regression model, believed to perhaps impact on the chances of receiving a radiograph, is the time that has passed from a patient's last visit to a dentist, *lastvisit*. The estimated models show a consistent and significant result across all model specifications and indicate that as the length of time between dental visits increases, so too does the likelihood that a radiograph will be given. As already noted earlier, the nature of this variable means that all patients' first visits are excluded from the sample and therefore those with only one visit are excluded. By design, these patients would have been excluded anyway in the fixed

[56] Note that *psex* will be dropped in models 5 and 8 due to the fixed effects transformation

effects models; however it is important to point out that, given the nature of the fixed effects transformation, those patients with only two visits are completely identified by their fixed effect. This means that it is not possible to separate out the relationship between other patient characteristics and radiograph behaviour, thus it is not possible to learn very much about the group of patients that tend to visit the dentist less often. The fixed effects estimates relate only to those patients with 3 or more courses of treatment in the sample.

5.3.4.2 Key Coefficients

In trying to account for the variation in the use of dental radiographs, one of the main concerns is the impact of the contract structure of the dentist. Another is the impact of demand side cost sharing i.e. whether a patient pays for their treatment or not. These effects can be estimated directly using the *se* and *exempt* variables, respectively. These will indicate if patients are more or less likely to receive radiographs if they are treated by a self employed dentist as opposed to a salaried dentist and if the fact that they pay (or not) for their treatment has any bearing on the treatment they receive. The inclusion of the interaction variable se*exempt in the model specifications means that a difference-in-difference estimator is also considered to assess the indirect impact of contract type, given exemption status. Before considering these key results, it is useful to recall the general model specification presented in section 5.3.2 above i.e.

$$y_{ik} = \mu + \mathrm{x}_{ik}\beta + \mathrm{u}_{jk}\gamma + \mathrm{w}_{ik}\eta + \mathrm{z}_{jk}\rho + \delta\left(\mathrm{w}_{ik}.\mathrm{z}_{jk}\right) + U_{ik} \qquad \textbf{(5.3.4)}$$

The inclusion of the interaction term in the model means that the interpretation of the coefficient estimates on the *se* and *exempt* variables i.e. ρ and η respectively is not one of the overall impact of dental contract and exemption status on the likelihood of receiving a radiograph. Essentially this only illustrates part of the overall picture. The coefficient estimates ρ, for example, show the impact of the dental contract for *non-exempt* patients only. Similarly the estimates η show the impact of exemption status for *salaried* dentists only In order to obtain the true impact of dental contract and patient exemption status, it is necessary to combine the estimates of ρ and η with δ (the coefficient of the interaction variable seexempt). $\rho+\delta$ is therefore the impact of the dental contract for *exempt* patients, and $\eta+\delta$ is the impact of exemption status for *self-employed* dentists.

Delta (δ) on its own can be classified as a difference-in-difference estimator and can be interpreted in two ways. It can either been seen as capturing the difference in the impact of contract type on the probability of getting a radiograph for exempt patients compared to non-exempt patients, or as capturing the difference in the impact of exemption status on the chances of giving a radiograph for self-employed dentists compared to salaried dentists. The latter of the two may be more relevant or intuitive than the first. It suggests that a positive δ implies that self-employed dentists are more sensitive to whether or not the patient pays for treatment or not i.e. they may give more radiographs to exempt patients than salaried dentists would.

Table 5.15 below presents a summary of the coefficient estimates across the model specifications of interest.[57]

[57] The results from the fixed effects specifications only are given, since they were always preferred over the random effects models

Table 5.15: Key Coefficient Results

	η (exempt)	(η+δ)	ρ (se)	(ρ+δ)	δ (se*exempt)
OLS	-0.0146	0.0079**	0.0047	0.0272*	0.0225
FEj	0.0054	0.0102**	-0.0009	0.0039	0.0048
FEi	0.0151	0.0227**	0.0225	0.0300	0.0075
FEiFEj	0.0102	0.0247**	-0.0178	-0.0034	0.0144

* Significance at the 5% level
** Significance at the 1% level

The results in Table 5.15 show a positive impact of exemption status on the likelihood of giving a radiograph for both self-employed and salaried dentists. The figures suggest that when a patient changes from being non-exempt and therefore paying for treatment, to being exempt and no longer having to pay, they are more likely to be given a radiograph (as indicated by estimates of η and $\eta+\delta$). A self-employed dentist will be between 1 and 2.5% more likely to give a radiograph, whereas a salaried dentist will be between 0.5 and 1.5% more likely to provide a radiograph, although in the case of a salaried dentist, the estimates are not significant. The magnitudes of the coefficients across model specifications also suggest that the patient fixed effects are important and should be considered. Models that control only for individual dentist specific effects are likely to result in coefficient estimates that are biased downward.

The results to analyse the impact of the dental contract on patients, captured by the estimates of ρ and $\rho+\delta$, do not give a clear message across the different specifications, and none are in fact significant. Some models show a positive relationship, whilst others show a negative relationship. The magnitudes of the coefficients across specifications, however, do again show the importance of controlling for both dentist and patient individual effects. In this case the importance of the dentist fixed effects is highlighted, as by not including them and modelling only patient effects, would give coefficient estimates that are likely to be biased upwards.

If it is assumed that the 3-way fixed effects error components model is to be 'preferred', then these results would indicate that when a dentist changes from being on a salaried contract to being self-employed, they are less likely to provide radiographs, regardless of whether or not the patient pays for their treatment or not. However, if the patient was exempt, they would be only 0.03% less likely to receive a radiograph, compared to being almost 2% less likely to receive a radiograph if they were a fee paying patient. This could again suggest that it is the self-employed dentists that are more influenced by whether or not a patient pays for treatment. This point is reiterated with the positive values of the difference-in-difference estimator, δ.

This interpretation does have to be treated with some caution given the insignificance of the estimates. It is very possible that the estimates are not well defined due to the lack of mobility in the sample. For the contract effects to be separately identified there has to be movement in the sample and a number of dentists would have to switch between contracts, and also treat a significant number of patients under both contracts. The precision of these effects is dependent on the number of movers and given this is only a small percentage; it is possible that the estimates are not well defined, hence the insignificant results. The strict exogeneity assumption of the model also means that there should be no endogenous moves of dentists from one contract to the other. If this assumption is not valid then the results are also likely to be biased.

Perhaps if there was more confidence about these estimates in the first instance, a further robustness check might be to estimate the probability that dentists change contract to see if there are any differences between self-employed dentists and salaried dentists. If there is evidence to suggest that they are different, dentists may be of a particular 'type' who are choosing to switch contracts, then this may have an influence on the estimated results. If this were the case, this would warrant further investigation to explore whether or not there are selection effects. Is it the case that dentists have a particular characteristic that makes them choose to change contract and is this impacting on the results?

There can be more confidence about the estimates regarding the impact of exemption status, as there are significantly more patients in the sample switching between being a payer and non-payer of dental treatment.

5.3.4.3 Dentist and Patient Fixed Effects

The results presented in Table 5.15 above highlight the importance of controlling for both dentist and patient unobserved time invariant effects in the model. As discussed in Chapter 3, AKM (1999) demonstrated that excluding either of these effects will result in what is equivalent to omitted variable bias. From Table 5.10, when considering the impact of exemption status, the importance of the patient unobserved heterogeneity becomes apparent, i.e. when only dentist heterogeneity is controlled for (FEj model), the estimates may exhibit downward bias. Similarly, the importance of controlling for dentist unobserved heterogeneity is clear when considering the impact of the dental contract on the use of radiographs. In this instance, models which control for only patient effects will give estimates that are likely to be biased upwards (see FEi model in Table 5.15). To try and eliminate any possible bias in the estimates, it is therefore necessary to use models that can control for both dentist and patient unobserved effects, as in the 3-way fixed effects error component model (FEiFEj).

The aim of this analysis was to try and not only identify, but also quantify potential sources of variation in the use of dental radiographs. The results presented above indicate the importance of not only observed factors but also the unobserved factors in contributing to the observed variation in radiograph provision. A key feature of the models chosen in this study is that they not only allow the researcher to control for unobserved heterogeneity but also to recover and analyse estimates of both the dentist and patient unobserved factors, thus giving a measure of actually how much they contribute to the observed variation.

The papers by Andrews et al (2006) and AKM (1999) demonstrate how the identification of the individual effects is only possible within groups – where groups are defined by, in this case, movement of patients between dentists. Each group will therefore exhibit patient mobility *within* it but not *between* groups. It is therefore only possible to compare the individual fixed effects within a group. It is also worth noting not all the dentist effects are identified i.e. no dentist effect will be identified in the case where no patients move between dentists and also within each sub group one dentist effect will act as the reference, with all other dentist effects being expressed as differences from this. Table 5.16 below shows the groups of dentists connected by mobility in the data sample.

Table 5.16: Groups of Dentists Connected by Patient Mobility

Group	Claims	Patients	Movers	Dentists
0	224	77	0	32
1	286,608	60,286	19,242	2299
2	7	4	1	2
3	4	3	1	2
Total	**286,843**	**60,370**	**19,244**	**2335**

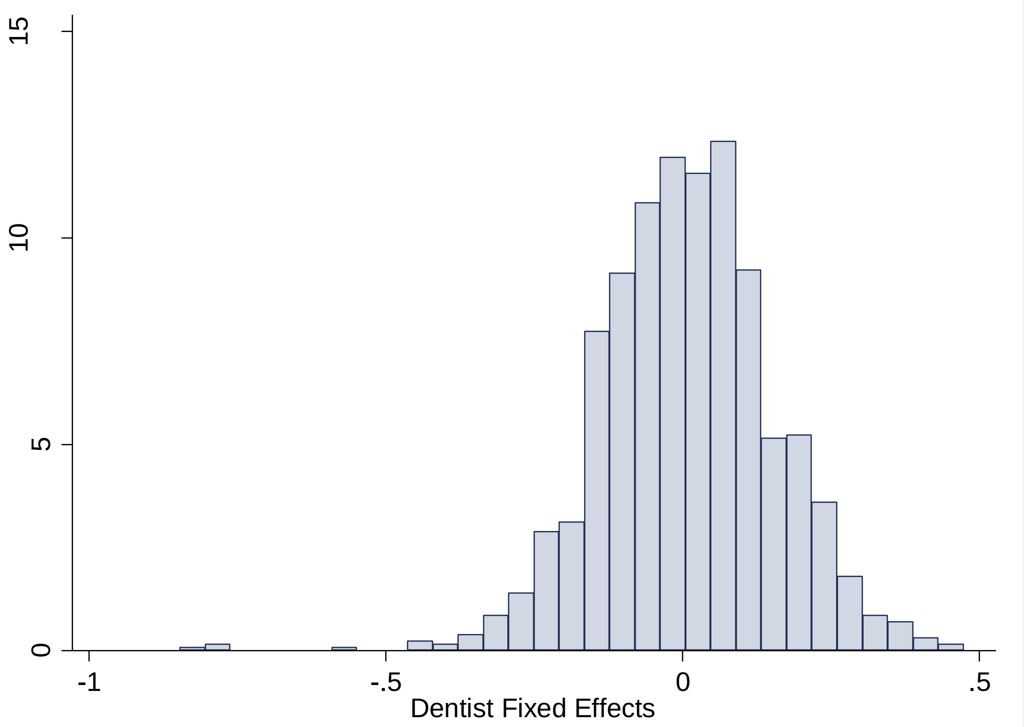
This shows that in this particular sample of dentists and patients there are only 3 groups where individual effects are identified. Group 1 contains the majority of the sample, whilst the other two groups are very small in comparison. Group 1 has 60,286 patients, where approximately 32% switch between 2299 dentists. Groups 2 and 3 are made up of only 2 dentists, with 1 patient moving between them. Given that most of the sample data falls into the same group, only group 1 fixed effect estimates are considered further.

These estimates are used to construct Figures 5.9 and 5.10 below, which plot the distribution of the dentist and patient fixed effects recovered from the estimation of the 3-way fixed effects error component model[58]. These distributions plot the percentage of dentists/patients that are more or less likely to provide/receive a radiograph compared to the reference dentist/patient, having controlled for all other observed characteristics of patients and dentists. They clearly illustrate the variation that exists across both dentists and patients and are useful at showing that all dentists and all patients do not behave in the same way. There are some dentists that behave similar to the reference dentist; however there are some dentists that behave very

[58] Note that the distributions of the dentist and patient fixed effects should be treated with some caution. For more information refer to page 166. Dentist fixed effects have been plotted for dentists with 50 or more movers (i.e. patients what have seen at least 1 other dentist) and the patient fixed effects have been plotted for patients with 10 observations or more.

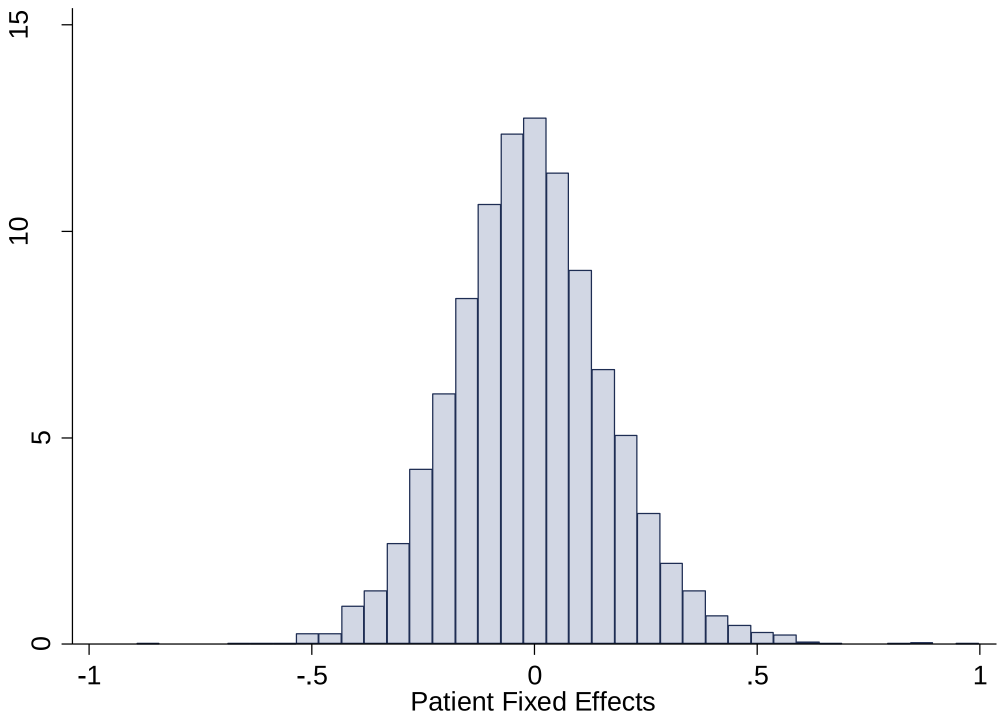
differently and will nearly always be less likely to provide a radiograph. This provides some support for the idea that unobserved individual characteristics specific to the dentist may make them behave quite differently to most other dentists. The results cannot say what these differences are, simply that they might exist. It may simply be due to time invariant dentist preferences which results in a given practice style.

Figure 5.9: Distribution of Dentist Fixed Effects



The same idea is true in the case of the patient fixed effects, presented in Figure 5.10. There are patients who are more likely to receive a radiograph compared to the reference patient, and those which are less likely to receive a radiograph. Again it is difficult to say what the actual driver of this variation is, but it is clear that after controlling for other characteristics such as age, gender and whether the patient pays for treatment or not there are still differences that exist across patients that result in different treatment patterns. This may be due to the underlying oral health of a patient, where some kind of ‘need’ warrants more radiographs, or in the case of those who get less radiographs, it may be due to a higher understanding or knowledge of the potential harmful effects from exposure to radiation, and there may be some resistance to being given an radiograph.

Figure 5.10: Distribution of Patient Fixed Effects



The empirical results presented in section 5.3.4.1 provide evidence to show that the dentist and patient fixed effects are both individually and jointly significant ($p < 0.01$). The model also provides information on the contribution of each effect to the observed variation in the probability of getting a radiograph. It suggests that the unobserved time invariant heterogeneity of dentists accounts for 5.2% of observed variation in the provision of radiographs, whilst as much as 22.5% of the variation can be explained by the unobserved time invariant patient effects. This suggests that patient variation is much more important in explaining total variation than dentist variation. This is a similar result to that found in both the labour and education literatures.

It is also possible to obtain an indication of the correlation between the patient and dentist fixed effects. AKM (1999) considered this in the context of workers and firms and asked the question, ‘Do High Wage Firms Employ High Wage Workers’. This can give some indication about the match between workers and firms, or in this case, dentists and patients. Is it the case that dentists with a high probability of providing a radiograph treat patients with a high probability of receiving a radiograph? The correlation between the two sets of fixed effects can help answer this. The results from the model show a small negative correlation (-0.3). This is a similar result to that found by AKM and it is not entirely intuitive. This suggests that, on average patients with a high probability of getting a radiograph sort themselves among dentists in such a way that they are treated by dentists who are less likely to provide radiographs. Woodcock (2008) proposes that these results of negative correlation are the result of bias in the estimated dentist and patient fixed effects. Woodcock proposes that match effects have to be included in the model specification to correct for this bias; otherwise estimates that omit match effects may be misleading. Woodcock demonstrates that the results found by AKM (1999) are overturned when the model specification controls for match effects. This presents an avenue for future work.

These results on the patient and dentist fixed effects should be treated with some degree of caution, given the way these individual effects are identified and determined. The unobserved patient effects are identified by multiple observations per patient, whilst the unobserved dentist effects are identified when there is mobility in the sample. The precision of these estimates are therefore a function of the number of observations per patient and the number of movers in the sample. The section on identification above (5.3.3) shows that a little over 30% of the patients in the sample move between dentists. It is this movement that allows for the dentist effects to be separately identified. The fact that there are a lot of movers in the sample, which does provide some support for the prevision of the estimates; it is actually the number of movers per dentist that adds to the accuracy of the results. Descriptives on the number of movers per dentist revealed that the numbers range from dentists with no movers' right up to dentists with almost 400 patients who have changed dentists, so there is some confidence there about the estimate that 5% of the variation in the provision of radiographs can be explained by unobserved dentist heterogeneity.

The accuracy of the results is also going to be very much dependent on the strict exogeneity assumption of the model and whether this holds or not. The descriptive statistics on movers versus non movers suggests that it is unlikely that there are large differences between the two groups of patients. Descriptive stats alone, however, cannot give us any indication of the accuracy of our estimates and the level of potential bias. This would have to be done by estimating separate models for movers and non movers and then determining if the coefficients are the same. If they are the same, this suggests that the results of the model can be generalised to non movers too. This would also lend support to the exogeneity assumption and would imply, for example, in relation to the dentist fixed effects, that the estimates of the dentist and/or patient fixed effects are picking up the effects of individual time invariant factors. For example, the probability of providing a radiograph might change as a response to the introduction of a new guideline on the provision of radiographs or a sudden trauma/accident that requires radiographs.

If it was found that the coefficients were widely different across movers and non movers, this would provide less confidence about the accuracy of the estimates and you would have to consider that the fixed effects are picking up some characteristic of the movers and not solely the time invariant characteristics of dentists and patients. One way of checking this would be to use a spell fixed effects estimation (as discussed in Chapter 3, section 3.4.3) and estimate separate models for movers and non movers. This was beyond the scope of this thesis but would be a good avenue for further research as it will provide a way of judging the accuracy of our estimates.

The estimate of 22.5% of total variation being explained by unobserved patient heterogeneity may not have the same support, as the sample sizes per patient are so small. Table 5.5 in section 5.2.4.6 illustrated that over 70% of the sample of patients have only 6 observations or less (the average number of courses of treatment per patient was 5). This could mean that the precision of the estimated patient fixed effects are not as accurate as they could be and the estimate of the contribution to overall variation may be compromised, thus 22.5% may not be the true value. Time constraints in this particular analysis meant this problem could not be explored further, but it could perhaps be investigated in future work. A larger random sample may help to increase the sample size per patient, or changing the sampling approach to oversample patients with many observations might be an option. This could help to improve the accuracy of the estimated individual unobserved patient heterogeneity and hence obtain a better measure of the patient contribution to overall observed variation radiograph provision.

5.4 Conclusion

This chapter provides a detailed description of the data to be used, which is essentially a matched patient provider dataset, similar to the ones described in Chapter 3. The data is taken from the Management Information and Dental Accounting System (MIDAS), a large administrative database used primarily to process the payments made to dentists, and contains detailed information of all dental treatment carried out and paid for in Scotland. Key features of the datasets become the key requirements for the type of analysis described above. Patient, Dentist and Course of Treatment (CoT) unique identifiers allow for the data to be *linked* and make it possible to track both patients and dentists over time, thus enabling estimation of models that can control for both dentist and patient individual effects (observed and unobserved).

A series of linear models are estimated so as to compare and contrast between them, with a view to being able to demonstrate the advantages of the three-way fixed effects error components model, hence identifying it as the ‘preferred’ specification for analyses of this type. This method resolves the issue of omitted variable bias and does allow estimates of the contributions of individual heterogeneity (dentist or patient) to the observed variation in the use of radiographs to be measured. Using the estimation framework described in Chapter 3 and the model specification presented in Equation (5.3.1) above, fixed effects models for three scenarios are estimated. These include the case with only patient fixed effects, only dentist fixed effects and controlling for both patient and dentist fixed effects. The empirical results emphasise the importance of including both in the regression model. From this point, discussions around the other results from the analysis will be restricted to the model with both patient and dentist fixed effects (FEiFEj).

The aim of this investigation was to analyse the variation in the use of radiographs across GDS dentists in Scotland. This has been done with a view of being able to account for both observed and unobserved factors. Of particular interest, was to analyse the impact of economic incentives on the treatment decision. The organisational framework in which dental care is provided in Scotland lends itself well to this as dentists operate under different remuneration systems and on the demand side some patients are fully insured from the cost of treatment. The results lend little support to what is typically found in the literature. Economists would predict that self-interested physicians working under a fee for service contract may deliver treatment that might not necessarily be in the best interest of the patient, but rather, in part due to some financial gain. This may be more likely in the case when the patient is in some way shielded from the cost of the treatment.

The results indicate that the remuneration structure has little or no impact on the treatment decision to provide a radiograph. When a dentist changes from being on a fixed salary contract to being paid on a fee-for-service basis, they are less likely to give a radiograph. This is regardless of whether the patient pays for their treatment or not. The results may suggest that the self-employed dentist places some weight on whether the patient pays for treatment or not as in the case when they are exempt from charges; they wouldn't be *as* less likely to give a radiograph than if the patient were a fee paying one. This interpretation has to be treated with some caution given the insignificance of the estimates and the fact that they may not be well defined, due to lack of mobility in the sample whereby dentists change contracts.

In considering the impact of exemption status on the probability of being given a radiograph, this is essentially like considering the impact of insurance in health care markets. The nature of the Scottish system means that all patients are to some extent insured from the cost of dental care, as fee paying patients only pay 80% of the full cost of provision, up to a predetermined maximum (currently £384). Exempt patients are therefore fully insured from the cost. The results given above show a significant positive impact of exemption status on the likelihood of giving a radiograph for self-employed dentists. This implies that when the only factor that has changed is that the patient went from being a fee paying one to not having to pay, self-employed dentists will be more likely to give that patient a radiograph. In fact there is also a positive result for the salaried dentist, though the results are not significant. Again, it appears as if self-employed dentists are more influenced by the exemption status of the patient than salaried dentists. There is more confidence in the estimates regarding the impact of exemption as there were significantly more patients in the sample switching from being a payer to being fully insured to the cost of treatment.

The evidence suggests that the fee-for-service payment structure provides no real incentive for self-employed dentists to provide more radiographs than salaried dentists. Andersen (2009) analysed the impact of professional norms and economic incentives on the behaviour and performance of Danish health care professionals, including dentists, GPs and orthopaedic surgeons. The results suggest that supply side incentives only matter when there are no firm professional norms surrounding a given treatment. If there are, it is likely financial incentives will have little or no impact on treatment decisions. This may be applicable here as radiographs are likely to be governed by strict guidelines and practices among the profession – therefore dentist behaviour is not influenced by any potential financial gain. It may also be that the potential gains are simply not great enough due to the relatively low cost of radiographs.

However, it could be argued that when the dentist can identify whether the patient pays for treatment or not, the self-employed dentist is motivated to provide more radiographs. It is likely that there will be less resistance from non fee paying patients and in a market of asymmetric information the dentist may be able to 'induce' demand. This approach assumes that ultimately it is the dentist that makes the decision about whether to provide radiographs or not. The result could also indicate a change of behaviour on the demand side. The theory predicts that in the presence of insurance in health care markets, patients demand more. (Pauly 1986) This result may support this idea and so when a patient no longer has to pay for treatment they may 'demand' more radiographs. This might be the case where patients are of the opinion that 'more' treatment means 'better' treatment, and now price is not a factor to consider. The results from the empirical analysis are consistent with both explanations.

Although the results are consistent with both explanations, there is little evidence in the literature to support the idea that patients will 'demand' more health care (particularly dental treatment). Given the nature of the dentist/patient relationship it is assumed that, even though the decision to treat may be a joint decision, the most influence comes from the dentist side, in the form of the dentist being able to learn about the characteristics of patients and make a treatment decision accordingly.

The first stage in the decision about whether to provide a radiograph comes from the dentist in relation to whether or not there is a clinical need to provide one – given it is the dentist who is much more informed about the oral health of the patient. Once this decision has been made then it is possible that other patient characteristics become important, but again only in so far as that the dentist will consider them when making the treatment decision. From the discussion presented in Chapter 3 (section 3.5.2) some of the other factors that are likely to impact on the treatment decision are:

- When did the patient last visit and did they have radiographs taken
- Does the patient pay for their dental treatment
- Are there constraints about actually doing a radiograph, for example, is the patient pregnant, is there time to do one, do are there many patients waiting?

There are both characteristics of the patient and the practice that the dentist takes into account when making the decision to provide a radiograph[59]. The decision is also influenced by the characteristics of the individual dentist, for example their practice style, opportunity cost of providing the radiograph (is there other treatments they could be doing that may be of more financial benefit to them or given there is a busy waiting room, will the decision to provide a radiograph impact on waiting times).

[59] For a more detailed discussion, refer back to Chapter 3, pp 57-60

The impact of remuneration contract and exemption status of the patient are two easily measured observable characteristics. A key component of this analysis was to consider the impact of unobservable characteristics on the probability of getting a radiograph. It is well established that unobserved individual heterogeneity needs to be taken into account in analyses like this. Often there are characteristics that are specific to either the patient or the dentist that cannot be easily measured, but will help to explain the observed variation in treatment. The estimation method used here allows the researcher to control for this in the model, but also enables an estimate of each contribution to be obtained. The results show that 5.2% of the observed variation in the use of radiographs is due to unobserved individual dentist effects, whilst the unobserved individual patient effects explain 22.5% of the variation in radiograph provision. The distributions of the dentist and patient fixed effects highlight the fact that the group of dentists in the sample behave very differently, as do the group of patients in the sample. The results show that there is widespread variation across dentists when it comes to the likelihood of a course of treatment containing a radiograph, because there is widespread variation in the types of patients that dentists treat. These differences are mainly unobservable and are likely to reflect patients' underlying oral health need and their preferences and attitudes.

The overarching aim of this study was to try to account for the widespread variation in the use of radiographs across dentists in Scotland (illustrated in Figure 5.1). Many studies in the field of health services variation have identified the existence of variation at many levels of the health care organisation, however not many have tried to explain the variation. This analysis identifies a number of potential sources of variation and attaches a measure against each one. Demand and supply variables (both observed and unobserved) are included in the regression model and the results show that the variation can be explained by four contributing factors:

- Dentist Fixed Effects 5.2%
- Patient Fixed Effects 22.5%
- Explanatory Variables 7.2%
- The Residual 65.1%

This information highlights the importance of patient heterogeneity as opposed to heterogeneity across dentists, a result that is also found in the labour and education literature.

The discussion above highlights that there are a number of characteristics, some observable, others not, that are likely to impact on the decision to provide an radiograph. Unfortunately, it has not been possible to include some of these desirable characteristics, particularly a measure of the clinical need of the patient, which is possibly central to the decision making process. Although a number of treatment categories are included in the regression models, as a way to try and account for a patient’s oral health, it is possible that this is not capturing the true effect (given the low level of explanation of the dependent variable in all specifications).

It might also have been better to include a variable to capture the level of experience of the dentist (maybe how long in practice, qualifications etc.) and where they trained to capture any practice style effects. Practice effects have also been identified as being important in the treatment decision and again they have not been considered separately in this model. The model in its current form is not separately identifying practice effects from the dentist effects, but in theory another level could be added to the estimating equation. Unfortunately, this will add a further level of complexity to what is already a complex model. In order to be able to identify the practice effects, dentists would have to move between practices. Although it is possible to identify dentists at the practice level in the MIDAS dataset, the extraction taken for this study does not contain any practice identifier. This approach may therefore represent an avenue for further research.

The analysis of the number of courses of treatment per patient that contained a radiograph (by way of the negative binomial regression) indicated that the probability of being provided a radiograph is positively associated with the number of courses of treatment that a patient has had. Patients who move dentists are also more likely to receive a radiograph straight after a move. These are important factors that are potentially not being picked up or are more difficult to see in the three way error components specification.

Although the model is likely to not be capturing all the factors that influence the variation in the provision of a dental radiograph, it is clear that patient characteristics are much more important in the treatment decision process, even if the final decision to provide the radiograph ultimately in most circumstances lies with the dentist.

If this is a true reflection of the decision making process, then there is support for my results in relation to the contribution of the variation being better explained by patient variation than variation across dentists.

Chapter 6: Conclusion

6.1 Main Conclusions and Implications for Policy

This chapter presents a summary of the main conclusions of the thesis and identifies potential avenues for further research. The implications of the findings are discussed in the context of economic incentives and unobserved patient and provider heterogeneity, and what this means for policy.

There is little doubt about the existence of variation in health care markets. In a literature spanning more than 60 years, it has been documented at all levels of the health care delivery process. Widespread variations are often considered to be a problem and raise questions about efficiency, equity and quality of care, in health care sectors facing ever increasing costs. There is wide recognition among governments and providers of health care (and insurance) of the importance of being able to identify the sources of variation, with a view to then being able to reduce it.

The idea that ‘cause dictates the remedy’ is certainly true in the case of medical practice variations. If the source and underlying cause of the variation can be identified, then governments and health care professionals are better placed to remedy the problem. For example, if the main driver of the variation is due to an underuse of known ‘effective’ care, this suggests that there may be patients who should be receiving a given treatment that are not. Ways to tackle this type of variation can include better guidelines surrounding clinical treatments, matched with some effort to ensure compliance with these guidelines. In the case where variation is driven by supply-sensitive services, a potential way to eliminate or reduce the variation is to re-design the payment system, from one which rewards ‘over’ care to one which rewards quality care. A policy of this type is now used within the NHS in England, by way of the Payment by Results framework.

The literature reveals a range of determinants that can aid explaining variation, all operating and interacting in a complex system. In the absence of a relevant theoretical model that can adequately capture these interactions, a slightly different approach to motivate the empirical analysis is adopted.

In the field of economics, the theoretical model is seen as a construct or conceptual framework that represents some real world economic process, by way of a set of variables and a set of logical relationships between them. They are most often designed to illustrate complex processes in a simple abstract way. The role of the empirical analysis is to then 'test' the proposed relationships of the theoretical model using real world data. In principal this all sounds straightforward and for many applications in economics this is a suitable framework for analysis. The problems lie when the theoretical models cannot and do not reflect the real world process under investigation. It is fair to say that a theoretical model is only useful to the extent that it mirrors the relationship it plans to describe.

In practice, in the real world there are many complexities to consider, and many of which are unobserved. In these situations Baker and Hubbard (2001) suggest that empirical testing strategies can follow one of two options; *"...either attempt to test the theory in the specific context of the theorist or look for other implications suggested by a more general application of the theory's main ideas".* This implies that one way to approach the empirical study is to use existing theoretical strands of the literature applied in the given context under study and to then generate some testable propositions. This is the approach that has been adopted for this thesis. A number of theoretical models that have been used to explain physician behaviour have been considered and the ideas taken to motivate an empirical framework in which the variation in the use of dental radiographs can be analysed. This approach allows for a number of hypotheses to be tested using the data.

Gaynor et al. (2001) conducted research to study the effects of physician incentives within organisations (HMOs). They identified that in order to conduct research of this nature, it relies on three key elements; one is detailed knowledge of the institutional context and the particular incentive scheme within; second is a model of behaviour that is tailored to this institutional setting and thirdly; rich detailed data drawn from within the organisation, on the outcomes under study. They argue that without all three elements, *"...the ability to draw inferences about the incentive system would have been limited".* Essentially this study provides a research setting similar to the one described by Gaynor et al. (2001). The discussion above, and that given in Chapter 3 on the empirical model, indicates that the model chosen is appropriate to the context. Chapter 4 of the thesis provides the detailed knowledge of the institutional context, and rich detailed data on the outcome (use of dental radiographs) is used in the empirical analysis.

Empirical studies that assess variation in health care often fail to produce satisfactory measurements of the actual contributions from different sources. This may be due to the fact that to actually achieve this, it requires a large amount of suitable data, with a particular structure, and estimation methods that can model the data in the correct way. This thesis presents an empirical framework from which this can be achieved. Much of the information has been borrowed from the field of labour economics where this type of framework has been developing over many years. It makes use of recent advances in micro-econometric modelling techniques and demonstrates how using such methods can lead to a better analysis of the variation in treatment decisions and/or outcomes in the field of health economics, by being able to control for *and* measure unobserved individual patient heterogeneity and unobserved individual provider heterogeneity at the *same* time.

The empirical analysis uses Scottish dental data (a matched patient provider dataset), taken from the Management and Information Dental Accounting System (MIDAS) to estimate a series of models to explain and account for the variation in the provision of dental radiographs. Fixed effects models are preferred to random effects models and estimation with fixed effects for dentists and patients is preferred to models that exclude one or the other. The model that includes both sets of fixed effects resolves the issue of omitted variable bias and allows for the separate contributions of individual heterogeneity (dentist or patient) to observed variation to be measured.

A review of the theoretical literature on incentives and physician agency helped to identify a number of hypotheses that could be tested to account for the variation in the provision of radiographs across GDS dentists in Scotland. On the most part these hypotheses are analysing the impact of economic incentives on the treatment decision, whilst hypothesis 4 considers the impact of individual dentist and patient heterogeneity and how much these factors impact on the treatment outcome. The results provide some support for what has previously been found in the literature, but only under certain conditions. Economists would predict that under a fee-for-service remuneration contract, there is an incentive to provide treatment that might be motivated by financial gains for the dentist, and not by what is in the best interest of the patient. The results indicate that the remuneration contract of the dentist alone has little or no impact on the decision to provide a radiograph. When a dentist changes from being on a fixed salary contract to being paid on a fee-for-service basis, they are in fact less likely to give a radiograph, although the results are not significant. However, the result is reversed in the presence of insurance. This can be defined as the case when the patient is exempt from the patient charge. In this instance the results are positive and significant (across all fixed effects model specifications) for self employed fee for service dentists, who thus are more likely to give a radiograph. This result provides some support to what has been previously found in the literature i.e. financial incentives can impact on treatment decisions.

It is likely that there will be less resistance from non fee paying patients and in a market of asymmetric information the dentist may be able to ‘induce’ demand. This approach assumes that ultimately it is the dentist that makes the decision about whether to provide a radiograph or not. Another way of looking at this result is to consider the result as indicating a change in behaviour on the demand side. The theory predicts that in the presence of insurance in health care markets, patients will demand more care, so when a patient no longer has to pay for treatment they may ‘demand’ more radiographs. This might be the case where patients are of the opinion that ‘more’ treatment means ‘better’ treatment, and now price is not a factor they have to consider. The results are consistent with both explanations; however given the information asymmetry evident in most health care markets, it could be argued that most patients will consume the care as recommended by their physician (Zweifel & Manning 2000).

A key component of this analysis was to consider the impact of unobservable characteristics on the probability of getting a radiograph. It is well established that unobserved individual heterogeneity needs to be taken into account in analyses like this. Often there are characteristics that are specific to either the patient (underlying oral health, aversion to dentist) or the dentist (practice style factors) that cannot be easily measured, but will help to explain the observed variation in treatment. The results highlight the importance of accounting for both unobserved patient *and* provider heterogeneity as this enables these effects to be disentangled from each other. The results suggest that patient variation is much more important in explaining total variation than dentist variation. This is a similar result to that found in both the labour and education literatures.

Given that it has not been possible to account for some important characteristics relating to patients and practices, the results should be treated with some degree of caution. It is likely that the major contributor in the treatment decision process is missing from the estimating equation, i.e. the clinical 'need' for a radiograph. This can be considered to be the very first step in the decision process. Although it is a patient characteristic, it is important in the decision in so far as the dentist has the information on this, which they use to decide whether to provide a radiograph or not. If this is a true reflection of the decision making process, then there is support for my results in relation to the contribution of the variation being better explained by patient variation than variation across dentists.

This particular finding has potentially important implications for policy. It relates back to the idea that 'cause dictates the remedy' in trying to deal with variation. This analysis allows for different sources of variation to be identified and suggests that a significant proportion of the observed variation in the use of radiographs is due to variation in patient specific effects. This can help inform the direction of any policy instrument targeted at reducing variation in the use of radiographs. If it can be identified that the main cause of variation is due to patient effects then policies to reduce variation should be directed towards patients, as opposed to dentists. One such example might be in the form of producing guidelines for patients that can increase their awareness about the need for and effects (potentially harmful) of dental radiographs. This will essentially enable a better informed patient to be involved in a shared decision process, which may help to reduce variation at the individual patient level.

One of the motivations for analysing variation in the use of radiographs was the possible harmful effects from exposure to radiation. Any suggestion that there might be some financial incentive for dentists to provide treatment that may not be in the best interest of the patient is particularly important in this context. The results from the model indicate that there is no real incentive for fee for service dentists to provide more radiographs than their salaried counterparts. The individual dentist effects do not account for very much of the variation, implying that dentist preferences or practice styles are not important factors in the decision about providing radiographs. This could suggest that dentists provide radiographs in line with the current guidelines and that the observed variation in their use is largely random or due to the different ‘types’ of patients dentists treat.

6.2 Avenues for Future Research

The novel aspect of this thesis is that it is the first to analyse the variation in the provision of dental radiographs using routinely collected individual data on dentists and their patients. It does so in a way that includes fixed effects for both dentists and patients, in a bid to control for, and measure their unobserved individual heterogeneity. This in itself provides the foundation for further research in this area. For example, this study considered only one type of radiograph; it might be useful to conduct a study that looked at all radiographs or, some of the other individual types. It would be interesting to see if similar results could be identified or if there might be other factors specific to radiograph type (for example cost) that changes the impact of incentives on the treatment decision.

There is a strand in the literature that is concerned about a possible link between dental radiographs and the risk of developing some types of cancer. Most of the existing studies in this area come with a range of caveats, particularly related to the way in which the data has been collected and the sample sizes involved. Typically the data is based on patient recollection, which may or may not be reliable. These studies recognise their shortfalls and indicate that more accurate detailed studies are required to better assess the risks. This would require information on the patients ages at the time the radiograph was provided, the frequency of radiographs carried out and the doses of radiation used. The framework used in this study could potentially provide such a setting to conduct this type of analysis. It would require that the MIDAS dental data be linked with patient cancer data. It may not be possible right now to conduct such a study but with the continued improvements in data collection and recording that is happening in Scotland today, it may be possible in the future.

Future research might address some of the limitations of this study. Some of the results have to be treated with caution as there is concern about how well defined they are. This is particularly true in the case of the estimated patient fixed effects as the sample sizes per patient are so small. This could mean that the precision of the estimated patient fixed effects are not as accurate as they could be and the estimate of the contribution to overall variation may be compromised, thus 22.5% may not be the true value. The same is true in the case when estimating the impact of the remuneration contract. These estimates are a function of mobility (i.e. dentists switching contracts) and the instances of this happening are relatively small in the sample. A larger random sample may help to alleviate these issues, or changing the sampling approach to oversample patients with many observations or dentists changing between contracts might be an option. This could help to improve the accuracy of the estimated individual unobserved patient heterogeneity and the impact of incentives on variation.

Practice effects have not been taken into account in this analysis, even though they are likely to have an impact on the decision to provide a dental radiograph. In principle, they could be incorporated into the analysis by adding another level to the estimating equation. Unfortunately, this will add a further level of complexity to what is already a complex model. In order to be able to identify the practice effects dentists would have to move between practices. Although it is possible to identify dentists at the practice level in the MIDAS dataset, the extraction that I have used for this study does not contain any practice identifier. Although possibly beyond the scope of this study it is something that could be addressed in further work. One concern I would have, however, is whether or not there would be enough dentists who change practice. The majority of dentists in Scotland are employed as independent contractors and essentially run their own business. If this work was to be conducted, it might be better suited to dentists in the salaried service or associate dentists who are more likely to move between practices.

Further work to consider/test the strict exogeneity assumption of the model would also serve as a good robustness check of this model and the results, for example the spell fixed effects estimation could be considered separately for patients who move between dentists versus those who are treated by the same dentist. In the case of identifying the contract effects it might be possible to estimate the probability that dentists change contract to see if there are any differences between self-employed dentists and salaried dentists. If there is evidence to suggest that they are different, dentists may be of a particular 'type' who are choosing to switch contracts, then this may have an influence on the estimated results. If this were the case, this would warrant further investigation to explore whether or not there are selection effects. Is it the case that dentists have a particular characteristic that makes them choose to change contract and is this impacting on the results?

Finally, this study could provide motivation for some further research on the theoretical aspects considered here. There is no doubt that the types of datasets used in this study, and described in Chapter 3, can broaden empirical research in the field of health economics, however at present it is difficult to find a suitable theoretical model that captures all the interactions considered in this analysis. One avenue may be to investigate the possibility of adding to/re-defining existing theoretical models that might better capture the complex processes of health care markets. The benefits of these large scale micro level datasets are obvious; however one consequence is that it leads to an awareness of the fact that some conceptual theoretical models have limited prospects for detailed understanding of the processes borne out by the data. This would provide an interesting, if yet challenging avenue for future research.

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Appendix

GP17 and GP17(0) Forms

NHS GENERAL DENTAL SERVICES REGISTRATION AND CLAIM FORM GP17 (10/08)

TO BE COMPLETED BY THE DENTIST IN BLOCK CAPITALS USING BLACK INK

Part 1 PATIENT INFORMATION

SURNAME

FORENAME

D.O.B. – – SEX M F

PATIENT IDENTIFIER

PREVIOUS SURNAME

ADDRESS

POSTCODE

Part 2 DENTIST'S INFORMATION

DENTIST'S NAME AND ADDRESS (STAMP)

Date of Registration/Acceptance for Treatment – –

Date of Completion of Treatment – –

Treatment on Referral

I claim payment under item 41B (Special Needs)

I do not wish to extend the patient's period of registration

Part 3 PATIENT CHARTING AND DETAILS OF CLAIM

8 8	7 7	6 6	E 5 5 E	D 4 4 D	C 3 3 C	B 2 2 B	A 1 1 A	A 1 1 A	B 2 2 B	C 3 3 C	D 4 4 D	E 5 5 E	6 6	7 7	8 8

Examination		Radiographs/Models		Scaling		Fillings	Deciduous	Deciduous		Dentists use only
1A	0101	2A1	0201	10A	1001	1401	4401	4403		£ p
1B	0111	2A4	0204	10B	1011	1402	4402	4404		
1C	0121	2B	0211	10C	1021	1403	Other Treatment (Free Replacements Tick Box A)		A	
Dentures		Crowns			1022	1404				
F/F	2730		1700	Endodontic		1421				
F/-	2731		1716		1501	1420				
-/F	2732		1721		1502	1422				
P/-	2733		1732		1503	1423				
-/P	2735		1734		1504	1426				
	2801		1782	Miscellaneous		1431				
	2802	Veneers			3611	Extractions				
	2771		1600		3631	2101				
	2772		1601		3701	2121	Referral (No. of claims)	4600		
	2738	Radiographs Available		Models Available			Trauma	TOTAL £		

355-2227 01010101 RR DONNELLEY B56198 05-08

TO BE COMPLETED BY, OR ON BEHALF OF, THE PATIENT
PLEASE USE BLACK INK

TO BE COMPLETED BY THE DENTIST

GP17 (10/08)

Part 4a PATIENTS DECLARATION ON ACCEPTANCE
I wish to be treated by this dentist under the NHS (General Dental Service) (Scotland) Regulations and will attend the Scottish Dental Reference Service if required.

I declare that the information I give on this form is correct and complete. I understand that if it is not, appropriate action may be taken. I confirm proper entitlement to exemption or remission. To enable the NHS to check I have a valid exemption/remission and for the purposes of prevention, detection and investigation of crime, I consent to the disclosure of relevant information from this form including to and by the NHS Business Services Authority, the Department for Work and Pensions, HM Revenue & Customs and Local Authorities.

I wish to be registered/continue to be registered with this dentist

I am registered with another dentist at this practice

I am registered with another dentist at another practice

I do not wish to be registered with any dentist

I wish to be treated by this dentist as a referred patient

Part 4b I HAVE TO PAY NHS CHARGES
I am liable for the NHS charge and may have to pay the full amount prior to treatment

I have or my partner has a current HC3 for partial help with NHS charges

I am the patient   I am the patient's parent, guardian or carer

Name in Block Capitals (if not patient)

Signature

Date

Part 4c I DO NOT HAVE TO PAY NHS CHARGES BECAUSE
I am under 18 years of age

I am aged 18 and in full time education

I am expecting a baby

I have had a baby in the last 12 months

I/MY PARTNER RECEIVE(S)

income related Employment Support Allowance**

Income Support**

Income-based Job Seekers Allowance**

I am/my partner is entitled to, or named on, a valid NHS Tax Credit Exemption Certificate**

I/my partner receive(s) Pension Credit guarantee credit**

**The name of the person receiving the benefit/credit if not the patient

D.O.B. or National Insurance No.

A current NHS charges certificate HC2 for full help with NHS charges   HC2 Number

Evidence not produced

I am the patient   I am the patient's parent, guardian or carer

Name in Block Capitals (if not patient)

Signature

Date

Part 5 REQUEST FOR PRIOR APPROVAL

I have examined the patient and seek prior approval to carry out the treatment detailed at Part 3 which I consider necessary.

Dentist's Signature

Date

Prior Approval Authorised

Part 6 DENTIST'S OBSERVATIONS

Part 7 DENTIST'S DECLARATION

I declare that the information I have given on this form is correct and complete and I understand that if it is not action may be taken against me. I claim payment of fees due to me for work carried out in accordance with NHS (General Dental Services) (Scotland) Regulations.

Dentist's Signature

Date

Part 8 PATIENTS DECLARATION ON COMPLETION
(To be signed by or on behalf of patient after treatment)

I confirm that I have had all the treatment I am willing to have and will attend the Scottish Dental Reference Service if required.
If you previously completed Part 4b but your circumstances have since changed and you do not now have to pay NHS charges please complete below:

On ‒ ‒ when the charge was made, I or my partner received one of the benefits/tax credits indicated at Part 4c or had a current NHS charges certificate which is indicated at part 4b or 4c.

The name of the person receiving the benefit/credit if not the patient

D.O.B. or National Insurance No.

I have paid or will pay the dentist (if you do not have to pay enter 00.00)   £

I declare that the information I have given on this form is correct and complete. I understand that if it is not, appropriate action may be taken. I confirm proper entitlement to exemption or remission. To enable the NHS to check I have a valid exemption/remission and for the purposes of prevention, detection and investigation of crime, I consent to the disclosure of relevant information from this form including to and by the NHS Business Services Authority, the Department for Work and Pensions, HM Revenue & Customs and Local Authorities.
I will pay the cost of the dental treatment if I am later found not to be entitled. In addition, a statutory penalty may be payable.

I am the patient   I am the patient's parent, guardian or carer

Name in Block Capitals (if not patient)

Signature

Date   PFTR

NATIONAL HEALTH SERVICE SCOTLAND

GP 17(O)
(Rev 10/08)

PART 1 TO BE COMPLETED BY THE DENTIST

SURNAME

FIRST FORENAME

DOB SEX(ENTER M or F)

ADDRESS

POSTCODE

Previous name if changed since last visit

PART 2

Dentist's Name, Address and List Number (Rubber Stamp)

[redacted]

NHS Number

Date of receipt for payment (For use by SDPB)

PART 3 **To be filled in by the patient. Please fill in and sign Part A or Part B. (If the patient is under 16 or cannot sign the form their parent, carer or other person responsible for them must sign.)**

I would like to have orthodontic treatment under the NHS. I understand that I may need to wear appliances. I am not having orthodontic treatment from another dentist under NHS. I agree to attend the Scottish Dental Reference Service if required.

Tick boxes that apply

A. If you have to pay:

1. I promise to pay the dentist the charges, if any, prescribed by Regulations made under the NHS (Scotland) Act 1978. I understand that I may have to pay all of the charges before the treatment starts.
2. I may be able to get help with the charges because my income is low, in the meantime I understand I have to pay................
3. I have, or am the partner of someone who has a current NHS charges certificate HC3 (Number) for partial help with NHS services. I have to pay the first £ of dental charges..........

I am: the patient the patient's parent, guardian or carer (please give details below)

Name (in BLOCK CAPITALS)..........

Relationship to patient..........

Signature.......... Date..........

B. If you do not have to pay: I do not have to pay NHS dental charges because:

1. The patient is under 16 .... E
2. I am under 18.......... F
3. I am aged 18 and in full time education (give School/College and Town).......... G
....
4. I am expecting a baby on (enter date in box)..........
5. I had a baby in the last 12 months (enter date in box)..........
6. I receive, or am in a family which currently receives, Income Support*..........
7. I am/my partner is entitled to, or named on, a valid tax credit exemption certificate* ....
8. I/my partner receive(s) Pension Credit guarantee credit*..........
9. I/my partner receive(s) income related Employment Support Allowance*..........
10. I receive, or am in a family which currently receives, Income-based Jobseeker's Allowance* M
*The name of the person receiving the benefit/credit is..........
11. I have, or am the partner of someone who has a current NHS charges certificate HC2 (Number) for full help with NHS Services .... N

Proof can be given if necessary.
I declare that the information I have given to the dentist is correct and complete.
Warning: I understand that a deliberately false statement may lead to prosecution.

I am: the patient the patient's parent, guardian or carer (please give details below)

Name (in BLOCK CAPITALS)..........

Relationship to patient..........

Signature.......... Date..........

To be completed by the dentist

Date of Acceptance for Treatment A

C Treatment on referral

D Number of Referral Claims

Date of Approval (For Use by SDPB) O

PART 4 A. Prior Approval

I have examined the patient and apply for the Board's approval to carry out the orthodontic treatment, which I consider necessary.

Dentist's Signature.......... Date..........

PART 4 B. To the Dentist – Approval Granted

Signed for the SDPB.......... Date..........

PART 5. To be signed by, or on behalf of, the patient after treatment

As far as I know the treatment has been completed.
I have paid, or undertake to pay, the total NHS charges for this course of treatment of.......... £
(If you do not have to pay enter 00.00)

Signature.......... Date..........

PART 6. To be completed by the dentist. *Delete as applicable.

*I have carried out all the necessary orthodontic treatment detailed and in my opinion the treatment has been satisfactory completed.

*Retention, where appropriate is continuing.

I claim payment of the fees due to me for the treatment specified.

Dentist's Signature.......... Date..........

Patient's charge £ p P

Patient's charge if different to P £ p Q

Date of Completion of Treatment R

355-2062

PART 7 E D C B A	A B C D E	
R 8 7 6 5 4 3 2 1	1 2 3 4 5 6 7 8	L
8 7 6 5 4 3 2 1	1 2 3 4 5 6 7 8	
E D C B A	A B C D E	

PART 8A Radiological analysis

Teeth: Unerupted | Absent | Supn. | Poor Prognosis

PART 8B Ceph analysis

SNA..............° 1 | 1 Max ....° 1 | 1 Mand ....°

SNB..............° FM/MM ....° APO ....mm

PART 9

Assessment 1. Angles Class 2. Skeletal Class

3. Overjet Positive mm Edge to edge Negative mm

4. Overbite % Incomplete Complete

Open bite (Indicate teeth involved)

5. Midline diastema mm 6. Crossbite (Specify teeth)

7. Centre lines (Relate to facial midline) (show by arrows any shift)

8. Path of closure centric

Mandibular displacement R L Forward

Teeth in premature contact

9. Soft tissues/habits (Give relevant details)

10. Tooth/bone relationship (Enter teeth) Spaced Crowded

PART 10 Treatment Proposals

Objectives

Extractions Teeth to be banded/bonded

Individual tooth movements

	Yes	No		
Correction of anterior occlusion				
			Yes	No
Correction of buccal occlusion A/P				
			Laterally	

RRD B54896 1/08 (071412)

PART 11 Relevent Medical/Dental/Orthodontic History

PART 12 Oral Hygiene Status

PART 13 Appliances

Removable Yes Number U L Fixed Yes Number U L

Type

Functional Passive U L

E.O.T. Yes Retention Fixed U L Removable U L

PART 14 Repairs (State details)

PART 15 Additional Information

Additional Information

Consultant Report (No / Yes)	No.	£	p	R Items
Item 1 a b c (ii)				
Item 2b (models) set				
Item 2b (models) dupl.				
Rads s m l opt ceph				
Item 32 (a) 1				
Item 32 (a) 2				
Item 32 (a) 3				
Item 32 (a) 4				
Item 32 (a) 5				
E.O.T				
Item 32 (b) 1				
Item 32 (b) 1 additional				
Item 32 (b) 2 removable retainer				
Item 32 (b) 2 fixed/bonded retainer				
Item 32 (c) 1 2 3 4				
Item 32 (d) specify at Part 15				
Other - specify Part 15				

T markers

V	£		2 9